UNIVERSITY OF PLYMOUTH

Autonomous Soil Analyser

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1. Abstract

The Autonomous Soil Analyser (ASA) is a modular device designed to automate and accelerate soil analysis for agricultural and environmental use as well as to help identify harmful and hazardous organisms in these fields. By integrating several sensors into a compact, user-friendly unit, the ASA aims to replace traditional, lab-dependant soil testing with rapid, on-site data collection and interpretation.

The device uses a combination of Nitrogen, Phosphorus and Potassium (NPK) sensors, moisture, temperature, pH, and electrical conductivity sensors to measure the health of soil. This is to provide farmers with data as to where deficiencies and issues are prevalent in the soil.

Linear actuators are used to probe the soil to detect obstacles such as rocks that must be avoided by the environmental sensors to prevent damage.

The secondary component of the ASA is the computer vision-based organism detection system that allows farmers to find plants and weeds that are dangerous to livestock such as ragwort. This system is powered by Bioclip which is used to detect, classify and geolocate the weeds using GPS, giving each instance a confidence score.

The entire system is placed on the Robotriks RTU which provides the ability to move across the field and gather data. This device also provides GPS locations to the main system and a power source from its 36V battery.

The system is run on a Raspberry Pi 5 using Python to interface the sensors, computer vision and the linear actuators. During run-time, the system will probe the ground to check for obstacles, it will then probe the ground with the soil sensors, and then pictures will be taken of the surrounding area to detect and classify harmful organisms. The data is then combined into a JSON file and saved to a removable external hard drive so that it can be post-processed to provide a detailed heatmap of the monitored agricultural area with a heatmap showing each of the collected metrics and locations of each hazardous organism.

The ASA is designed to provide farmers with more informed, data-driven, and actionable approaches to soil science to tailor inputs such as fertilizers and irrigation based on real-time soil conditions by promoting efficient resource use and reducing environmental impact.

2. Acknowledgements

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3. Introduction

In the modern day, farmers are under constant pressure to deliver high crop yields and environmental farming practices. Effective monitoring of soil properties is critical for optimising agricultural productivity and ensuring sustainable land management. Traditional soil analysis techniques typically rely on laboratory testing, which can be slow, resource-intensive, and infrequent limiting their ability to inform real-time decision-making in the field. Livestock is also harmed by the presence of dangerous weeds such as Ragwort which can easily harm horses or cows if ingested.

The Autonomous Soil Analyser (ASA) has been developed to address these challenges by enabling automated, on-site collection of important soil metrics. The system integrates a range of sensors to measure nitrogen, phosphorus, and potassium (NPK) content, as well as soil pH, moisture, temperature, and electrical conductivity. These parameters are among the most significant factors in determining soil fertility and crop suitability. Real-time access to this data allows farmers to adjust what they add to the soil, improving fertiliser efficiency and reducing environmental impact based on their choice of crop or land use.

Furthermore, a computer vision-based system using the Bioclip classifier has been integrated to constantly take images across the monitored site. These images are cross-referenced with a list of arable weeds pervasive in the UK and are flagged if detected.

The ASA platform contributes to precision agriculture by enabling a holistic health analysis across agricultural fields. Sensor readings and weed detection is combined with GPS coordinates to allow post-processing and visualisation through geo-tagged heatmaps. This supports informed decisions regarding fertilisation, irrigation, and livestock roaming. The system also assists in environmental monitoring, providing a means to detect nutrient imbalances, salinity issues, or soil degradation trends at an early stage.

To support autonomous operation, the sensing module is mounted on the Robotriks RTU V4, a platform which provides mobility, power, and GPS functionality. A linear actuator mechanism mounted to this platform allows the sensors to probe the soil at multiple depths with height adjustments, while also detecting and avoiding subsurface obstacles.

The following report outlines the design and implementation of the ASA system, with a focus on its sensor integration, computer vision module, soil actuation and data management. System performance is evaluated through specific sensor tests, and the report concludes with a critical analysis of limitations and future development opportunities.

4. Background

4.1 Plant Identification

4.1.1 Bioclip

Bioclip is an open-source artificial intelligence model trained on the tree of life dataset. The tree of life data set is currently the most diverse machine leaning ready data set available, making it useful for our application. Bioclip is based on Open AI’s “Clip” [1] which is a neural network model designed to learn visual concepts from natural language supervision. Using Bioclip s deep neural network it can extract and analyse visual features from images, to identify specific plant species or classes.

By focusing on minute morphological details, Bioclip delivers high precision in identifying plant species. This is critical in our project where the accurate differentiation between hazardous weeds and non-target flora can significantly influence soil management practices.

Bioclip is engineered to perform reliably under varying environmental conditions, such as fluctuating lighting and background clutter. This robustness ensures that the system maintains its accuracy even in dynamic field environments where our mobile unit operates.

4.1.2 Encyclopaedia of arable weeds

The encyclopaedia of arable weeds [2] is a list curated to identify common weeds to the UK. The list details pros and cons of each weed as well as their type, what they are competitive with, what herbicides they are resistant to and other relevant information to aid in land management. The wide range of species identified in the encyclopaedia is used in the project to help landowners in become aware of the plant life and its hazards. The encyclopaedia of arable weeds bridges the gap between the automated image analysis and a large knowledge base required to assist land management.

4.2 Soil Health Measurements

Soil health is a foundational factor in determining the productivity and sustainability of agricultural systems. It encompasses the biological, chemical, and physical conditions of soil, all of which influence plant growth, nutrient cycling, and water retention. To effectively manage land for crop production, it is essential to monitor key soil parameters that provide insight into its fertility and structure across the growth of multiple crops and land uses.

Farmers would have to send samples of soil across the field, by manually digging and packing, to labs and getting nutrient composition readings several weeks or months later. The following readings are usually taken in labs, but the ASA seeks to do this all rapidly and on site.

4.2.1 Importance of NPK

Nitrogen, phosphorus and potassium are important macronutrients for the growth of crops and plants in general as nitrogen is responsible for promoting leaf and stem growth, phosphorus is needed for energy transfer processes and flowering in plants, and potassium is required for water uptake and retention in plants as a few of the benefits; therefore, an adequate composition of these elements is required to nurture healthy crops according to [3]. The sensors measure these elements in terms of mg/kg or ppm. Correlating the measured values to the ideal values depends on the crop needed to be grown depending on the farmer’s use case. For example, leafier plants like spinach may need more nitrogen, however fruit producing plants such tomatoes will require more potassium. Tomorite is a fertiliser for tomatoes that has a 4-3-8 NPK ratio to grow tomatoes in comparison to a standard 5-5-5 ratio for most generic plants according to [4].

4.2.2 Importance of pH

PH is critical as it can determine whether a crop will fail or thrive. A pH of 4.0 which is highly acidic will result in most crops failing. The optimal pH of soil differs between soil type as well as the crop grown. An example of this is when doing continuous arable cropping: mineral soils have an optimal pH of 6.5, peaty soils have an optimal pH of 5.8, organic soils have an optimal pH of 6.0, and subsoils have an optimal pH of 6.3. The target pH for the soil is ideally 0.2 pH above the optimum with reference to [5]. During testing, the soil type will be pre-determined before sampling as the system is not specified to identify soil types. When measuring the soil pH, values of 6.0-7.5 is acceptable for most plants as nutrients the required nutrients are most abundant in that range according to [6].

4.2.3 Importance of Temperature

Temperature is a crucial factor in crop growth as various common crops require different conditions such as spring wheat which requires a minimum temperature of 3°C, soybeans which require a minimum temperature of 15°C, and plants such as tomatoes require an optimal temperature of 16°C [7]. This is because plants have varying seed germination rates, enzymatic reactions, and microbial processes. Monitoring this parameter is particularly important for timing planting and fertiliser application.

4.2.4 Importance of Moisture

Monitoring moisture levels is critical to make sure that crops can absorb enough water and to prevent too much water from being lost (up to 85%) from evapotranspiration. The optimal moisture level differs based on the climate. For example, when concerning UK temperate climates: 10°C (cold) days require 1-2mm of water per day, 20°C (moderate) days require 2-4mm of water per day, and 30°C (warm) days require 4-7mm of water per day. Research for this data is from [8].

4.2.5 Importance of Electrical Conductivity

Electrical conductivity (EC) serves as an indicator of soil salinity. Elevated EC values can signal poor drainage, salt build-up, or over-fertilisation, all of which can stunt crop growth and degrade soil over time.

4.3 Actuators

Linear actuators are electromechanical devices that convert rotational motion into linear displacement, allowing for precise movement along a single axis. In automation, they are commonly used for positioning tools or sensors with high repeatability and minimal human intervention. For the Autonomous Soil Analyser (ASA), linear actuators play a crucial role in both sensor deployment and environmental hazard mitigation. Within the ASA system, two linear actuators are employed. The first is dedicated to probing the soil to detect subsurface obstacles such as rocks, while the second is used to insert the sensors into the ground to gather accurate readings of soil health. This two-stage probing mechanism ensures that fragile sensors are only deployed when the system confirms that the ground is clear of any rocks or obstructions.

Electric linear actuators were selected for their compatibility with the Raspberry Pi 5, which serves as the central processing unit of the ASA. These actuators are controlled using GPIO pins via H-bridge motor drivers, allowing for bidirectional motion. Their compact form factor, low power requirements, and straightforward integration with Python-based control software make them an ideal choice for embedded systems operating in field environments.

A key feature of the actuator-based rock detection system is its ability to monitor the current drawn by the motor during movement. If a spike in current is detected indicating increased resistance, due to a rock or other obstruction, the actuator immediately retracts. This feedback loop, enabled by a current sensor (INA219), reduces the risk of damage to the actuator or the sensors and allows the system to reposition before attempting another probe.

Importantly, the actuators used in the ASA are supplied with built-in waterproofing rated at IP42. This ensures that they are resistant to dirt ingress and rain, making them well-suited to outdoor environments where exposure to moisture, rain, or damp soil is likely. Their sealed housings protect internal components from corrosion and mechanical failure, improving reliability and reducing maintenance requirements during long-term deployment in the field.

The use of linear actuators allows for consistent and accurate depth control during soil sampling, which is essential for acquiring comparable readings across different locations. Their inclusion in the ASA contributes significantly to automation, enabling the system to operate independently across large areas with minimal intervention. While highly effective, actuators must be calibrated to account for varying soil densities and may require adjustments to maintain sensitivity in particularly rocky or compacted terrains.

5 Requirements Capture

This section evaluates the degree of success the ASA project is implemented in relation to the specifications outlined in the Project Execution Plan (PEP).

5.1 Soil Compaction

The first major requirement of the ASA project was to implement soil compaction measurement by probing to a depth of 15–30 cm, recording actuator force versus penetration depth, generating a force map, and classifying soil as soft, medium, or hard with corresponding density values in g/cm^3. While the linear actuator reliably drove the probe to selectable depths and used current feedback to detect obstacles, the calibrated mapping from applied force to a quantitative density metric was never completed. As a result, the system cannot yet report actual soil density or apply the soft/medium/hard labels envisioned in the original proposal. Soils with low bulk density are generally more suitable for agriculture, since the high pore space has a greater potential to store water and allow roots to grow more readily [9].

5.2 Soil Component Sensing

In contrast, the soil component sensing subsystem fully met its specification. The ComWinTop 7-in-1 sensor was integrated and successfully measured nitrogen, phosphorus, potassium (in ppm), moisture content, temperature, pH, and electrical conductivity at depth. All readings were logged as JSON and later rendered into georeferenced heatmaps, providing farmers with clear, actionable data. Although calibration at very high nutrient concentrations could be refined further, the sensor delivered accurate, repeatable results across the low-to-moderate ranges critical for field management.

5.3 Weed Detection

The weed detection requirement by capturing images, classifying hazardous species such as ragwort using the Bioclip model, and mapping detections with GPS coordinates was partially achieved. The onboard camera and processing thread reliably acquired images and produced confidence scored classifications, storing both images and metadata on an external drive. However, the integration of live GPS data into the image metadata was not realised; spatial tagging must currently be applied offline during post-processing.

5.4 Power Supply Integration

Power integration from the RTU battery rails (5 V, 12 V, and 36 V) was not accomplished, despite being specified in the proposal. All electronics were powered via wall-plug supplies due to unresolved interfacing issues with the RTU's power breakout connector. As a result, the system lacks true field autonomy and remains tethered to external power during testing.

5.5 Data Usage and Visualisation

Data usage and visualization objectives were fully satisfied. Sensor and camera outputs were aggregated into structured JSON files, and standalone tools successfully generated geo-referenced heatmaps of soil metrics and organism detections. Farmers can thus visualise spatial patterns of soil health and weed distribution as intended.

5.6 Mobility and Platform Integration

Mobility and platform integration saw mixed results. The ASA hardware was successfully mounted on the Robotriks RTU v4, and basic motion control was demonstrated. The software includes sampling logic with 5 m intervals, but full autonomous navigation with W-Sampling and RTU GPS guidance has not been field-validated, leaving end-to-end path following incomplete.

5.7 Operational Environment

Environmental and operational requirements, reliable operation on slopes up to 20° in dry conditions between 5–20 °C were only partially exercised. The RTU was taken out only on level, dry terrain within the specified temperature window. However, robustness against inclines, precipitation, and extended field exposure (e.g., waterproofing) was not fully tested for the mounted ASA system.

5.8 Sampling Methodology

Finally, the sampling methodology requirement called for obstacle-aware, distance-based sampling using a W-pattern. Obstacle detection successfully prevented actuator damage, and the software supports both distance-triggered measurements, but it doesn't support W-pattern trajectory due to GPS and control limitations.

5.9 Requirements Summary

In summary, the ASA met its core goals of in-situ soil component sensing and data visualisation, while the soil compaction mapping, RTU power integration, GPS-enabled navigation, and full environmental testing fell short of the original specifications. Addressing these gaps in subsequent development phases will be essential to realise the project’s full vision.

6 Analysis and design

This section of the report focuses on the overall build of the ASA as well as the design and reasoning behind each of its subsystems.

6.1 Components

The following section describes the selection of each component to build the ASA, the reasoning behind the specific component, the data that is gathered, and the costs associated with each component.

6.1.1 Camera

To ensure seamless integration with the rest of the system, the selected camera needed to be fully compatible with the Raspberry Pi. Additionally, it had to withstand constant motion and vibrations experienced by the RTU during operation. Image quality was another critical factor, as the captured data would be processed by a plant classification algorithm. The Tree of Life classifier used within the Bioclip framework was trained on a diverse dataset with varying image resolutions. As such, a resolution of at least 720p was sufficient to produce reliable classification results.

Given the dynamic environment, the camera’s ability to maintain focus was a key consideration. The Ardu 16MP Autofocusing Camera [10] was selected for its high-resolution output and native compatibility with the Raspberry Pi. It autofocusing feature enables it to consistently capture sharp images and videos without manual adjustment, even in the presence of motion. This allows the system to operate autonomously for extended periods while maintaining the image quality required for accurate plant identification.

6.1.2 Raspberry Pi 5

The Raspberry Pi 5 [11] was chosen to be the central computer handling all processes in the system as it is small, modular and the fastest production Pi released to date. It features a quad-core ARM Cortex-A76 2.4GHz processor allowing for multithreading in terms of computer vision tasks, sensor measurements and actuation signals simultaneously. The Pi also has 8GB of RAM so that all these processes can be run as well as running a developmental IDE such as Visual Studio Code. 3 of these units were purchased so that each group member could separately work on their component on the Pi before integrating them together.

The Pi 5 also has full GPIO access, which allows for direct interfacing with low-level hardware such as H-bridges, current measurement units and linear actuators. This allows for tighter polling timings and custom control logic. It also has access to 4 USB ports which means that it can interface with the camera, serial adapter, hard drive, and general peripherals if debugging is required.

The Raspberry Pi OS (Linux) has full support for Python libraries that are required for this project such as OpenCV-Python, NumPy, serial, and lgpio. The inclusion of a Wi-Fi chip allows the system to be controlled without the need of a mouse and keyboard using VNC viewer or SSH when running autonomously. This also supports apps such as GitHub Desktop so that code can be written easily on a PC and pulled down to the ASA system efficiently.

The Pi 5 consumes less power than a desktop PC or laptop as it only requires a 5V 5A power supply. This also allows it to be powered by the RTU battery mentioned later. This allows long term operation in agricultural environments.

6.1.3 7-in-1 NPKTHPHEC Sensors

The 7-in-1 NPKTHPHEC RS485 sensor by ComWinTop [12] was selected as it provides a comprehensive package of readings and metrics in a single compact unit. The sensor integrates measurements for nitrogen (N), phosphorus (P), potassium (K), temperature, humidity (moisture), pH, and electrical conductivity (EC), offering a comprehensive dataset for agronomic analysis while reducing system complexity and wiring overhead.

Temperature Sensor:

- Range: -40°C to 80°C
- Accuracy: ±0.5°C
- Long-term drift: 0.1%/years
- Response time: 15 seconds

Moisture Sensor:

- Range: 0–100% volumetric water content
- Accuracy: ±3% (below 50%), ±5% (above 50%)
- Drift: 1%/year
- Response time: 4 seconds

Electrical Conductivity (EC) Sensor:

- Range: 0–20,000 µS/cm
- Accuracy: ±3% (below 10,000 µS/cm), ±5% (above 10,000 µS/cm)
- Drift: 1%/year
- Response time: 1 second

PH Sensor:

- Range: 3.0–9.0 pH
- Accuracy: ±0.3 pH
- Degradation: ~5%/year due to probe corrosion
- Response time: 10 seconds

NPK Sensors:

- Range: 0–2999 mg/kg (ppm) for each nutrient
- Resolution: 1 mg/kg
- Response time: <1 second
- Manufacturer does not specify long-term drift or accuracy.

This integrated sensor significantly streamlines the system design by minimizing the number of discrete components required, reducing potential failure points and simplifying calibration and data management. Its wide measurement ranges and real-time response times are well suited to agricultural applications where soil properties can vary across short distances.

6.1.4 RS485 Adapter

To allow the soil sensors mentioned above to communicate with the Raspberry Pi 5 without using the GPIO pins currently dedicated to the actuator hardware, a dedicated RS485 to USB adapter is implemented to facilitate serial communication from the sensors to the Pi using the serial library in Python.

This uses the Modbus protocol over the RS485 physical layer to send data from each sensor encoded as hexadecimal values, where each measurement is 2 bytes of data being transmitted to enable structured and efficient data handling.

The benefits of this implementation are the availability of GPIO pins for other functions, independent debugging, and testing of sensors by only monitoring the given serial terminal, full driver support using the serial library, and cable length flexibility if implementing the ASA on other mobile platforms. This system improves the modularity, scalability, and reliability of sensor integration in the system.

6.1.5 Linear Actuators

Two linear actuators are implemented in the ASA system to facilitate soil probing in a controlled and autonomous manner. The first actuator is used to assess whether the ground is suitable for sensor insertion by detecting the presence of obstacles such as rocks or compacted soil. The second actuator is then responsible for inserting the multi-parameter soil sensor once it is confirmed that the area is clear of obstructions.

The actuators selected for this system are RS PRO Micro Linear Actuators ` [13], with the following specifications: 300 mm stroke length, 24 V DC input, 3000 N thrust force, and a travel speed of 8.3 mm/s. These units provide the high force and precision required for reliable probing across varying soil types.

During the rock detection phase, the obstacle detection actuator is deployed forward into the ground. The current consumption of the actuator is continuously monitored using the INA219 current sensor. If the current drawn exceeds a pre-defined threshold, this indicates an increase in resistance suggesting that a hard object such as a rock has been encountered. Upon detection of this condition, the actuator is immediately retracted to prevent potential damage, and the system moves to test a new location.

These actuators are controlled via H-bridge motor drivers, with direction and speed managed through GPIO signals from the Raspberry Pi 5, enabling precise and responsive control integrated with real-time current feedback.

6.1.6 H-Bridges

To enable directional control of the actuator used in the ASA system, H-bridges were used. A H-bridge is an essential component for controlling DC motors, as it allows the polarity of the voltage to be reversed. This is critical in the ASA where actuators need to be extended and retracted as part of the soil probing and obstacle detection processes.

The H-bridge module selected for this system is the Hyuduo Motor Drive Module Board, featuring a dual BTS7960 high-current (43 A) H-bridge driver [14]. This module was chosen for its ability to handle the high current requirements of the RS PRO linear actuators (up to 3000 N of force), providing reliable and efficient motor control under varying soil load conditions.

During the rock detection phase, one of the actuators are probed into the ground. current consumption of the actuator is continuously monitored using the INA219 current sensor. If the current drawn exceeds a pre-defined threshold, this indicates an increase in resistance, suggesting that a hard object such as a rock has been encountered. Upon detection, the actuator is immediately retracted to prevent potential damage, and the system is repositioned to test a new location.

The H-bridges are concealed within a waterproof container, so they are protected by the elements.

The H-bridge is controlled using GPIO headers on the raspberry pi. This allows for autonomous soil probing with dynamic obstacle avoidance, contributing to the overall reliability and resilience of the ASA system.

6.1.7 Current Measurement Unit

To monitor the electrical current drawn by the linear actuators during operation, the INA219 high-side current sensor was used. This module enables real-time current and voltage monitoring, which is essential for the ASA's rock detection system, where a sudden spike in current indicates that the actuator has encountered an obstacle such as a rock or hard soil.

The INA219 [15] was selected due to its high accuracy, low power consumption, and ease of integration with the Raspberry Pi 5 via the I²C communication protocol. As a digital sensor, it provides current, voltage, and power readings directly over I²C, which simplifies the hardware design and minimises the number of GPIO pins required.

Operating as a high-side current sensor, the INA219 is placed between the actuator's power supply and the H-bridge input. This allows it to measure current without disrupting the ground path, improving reliability and accuracy in field conditions. The sensor is capable of measuring currents up to ±3.2 A and voltages up to 26 V, making it suitable for the 24V, 2.8A actuators used in the ASA system.

In the ASA application, the Raspberry Pi continuously polls the INA219 during actuator motion. If the current reading exceeds a defined threshold, the Pi interprets this as resistance due to an obstacle and commands the actuator to retract. This feedback mechanism allows for intelligent and autonomous probing, reducing the risk of mechanical damage to the sensor system.

6.1.8 External Hard Drive

A Seagate 1TB external hard drive [16] was selected as the primary mass storage for the ASA system. This is so that high-resolution images captured can be stored as well as the constantly appended JSON file for sensor and GPS data during the ASA's monitoring and sweeping of agricultural land.

An external hard drive such as this provides easy connection via USB to the Pi and allows the drive to be easily removable so that the data can be post-processed for plug-and-play compatibility. HDDs offer greater endurance and longevity than microSD cards with high-speed data transfer (125MB/s).

6.1.9 Mobile Platform

The system's mobility is provided by the Robotriks RTU V4 [17], a versatile robotic platform suited for navigating farmland terrain. This platform also serves as the primary power source for the system, supplying the necessary voltage levels (36V, 12V, and 5V) to operate the various components effectively. It also has a GPS chip allowing the drivetrain to be directed according to set coordinates provided. The GPS data can then be sent to the Pi 5 for geotagging either via a direct serial connection or 433MHz radio transmission.

6.1.10 Budget

This section provides an overview of the budget allocated for the Autonomous Soil Analyser (ASA) project, detailing the components acquired, costs incurred, and the items used versus those that were not integrated into the final system. The total budget for the project was £1200, with 88.6% of it spent, leaving a remaining balance of £136.55. Below is a table of all components that were purchased disregarding delivery costs.

Table 1 - Expenditure

Component	Quantity	Cost per Unit (£)	Total Cost (£)	Degree that it is used
Raspberry Pi 5 8GB	3	76.50	229.50	Used in system
Raspberry Pi 5 Active Cooler	1	4.50	4.50	Used in system
Raspberry Pi 5 Display Cable	3 (2m x 1, 1m x 2)	5.80 + 2 x 3.80	13.40	Used in testing
Raspberry Pi 5 Power Supply	3	11.40	34.20	Used in system
RS PRO Micro Linear Actuator, 300mm, 24V dc, 3000N, 8.3mm/s	1	116.46	116.46	Used in system
Seagate 1TB External HDD	1	46.99	46.99	Used in system
10A 2-Channel 7-30V DC Motor Driver for RC	1	36.80	36.80	Not used
Arducam 16MP Autofocus USB Camera	1	72.50	72.50	Used in system
D-sub Connector DB9 Female Socket 9-pin Female Serial Port Terminal Breakout	1	7.19	7.19	Used in system
DC Stepper Motor Driver Module 43A Current Limit Control Module H-Bridge	2	12.99	25.98	Used in system
RS485 output Soil Nitrogen Phosphorus Potassium PH Conductivity EC Temperature Humidity Moisture Sensor	2	76.04	152.08	Used in system
ABB IP65 Junction Box	1	25.60	25.60	Used in system
Soil Testing Kit	2	9.59	19.18	Used in testing
HOLMOL Threaded Inserts for Plastic 360PCS	1	12.98	12.98	Used in system
Knurled Embedment Nuts	2	13.99	27.98	Used in system
Potting Compost Enriched with Nutrients-Expands	1	14.99	14.99	Used in testing
RS PRO Circular Connector, 5 Contacts, Cable Mount, Plug, Male, IP68	2	17.98	35.96	Not used
Deltaco USB 2.0 USB A to USB C	1	6.08	6.08	Not used
Circular Threaded Connector Plug, 3-Pole, 5-8mm, IP68	4	3.30	13.20	Not used
RS PRO Circular Connector, 5 Contacts, Cable Mount, Plug and Socket, Male and Female Contacts, IP68	1	24.56	24.56	Used for future upgrades

Adafruit RFM69HCW Transceiver Radio Bonnet - 433 MHz (RadioFruit)	1	29.19	29.19	Used for future upgrades
56800mAh 65W Solar Power Bank Large Battery Pack	1	44.87	44.87	Not used

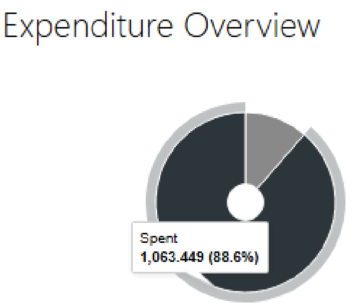


Figure 1 - Expenditure Overview

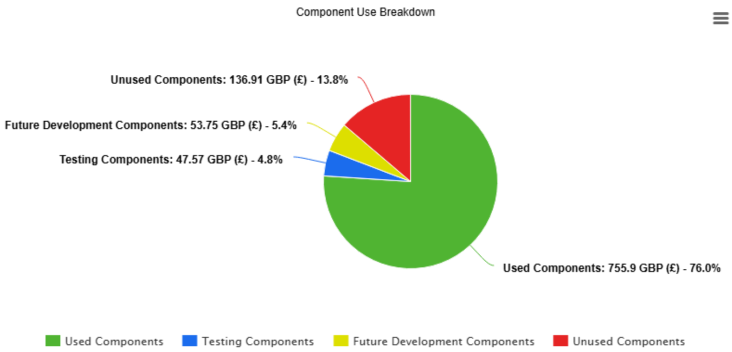


Figure 2 - Component Use Breakdown

To summarise the financial breakdown, the project stayed within the allocated budget of £1200, with £136.55 remaining after all essential components were purchased and implemented. Overall, 76% of acquired components were directly useful to the final ASA system, contributing to core functionality such as sensing, actuation, and data storage. An additional 4.8% were used during testing and development, helping validate subsystems even if not present in the final assembly. 5.4% of components such as the 433 MHz radio module were not integrated but remain viable for future system upgrades. The remaining 13.8% were unused, mostly due to changes in design scope or integration challenges. Despite these minor inefficiencies, the project remained cost effective and scalable, with clear opportunities for refinement in future iterations.

6.2 Plant Identification

The plant identification software is designed to utilise the artificial intelligence model Bioclip [18]. Bioclip identify' s plant species and classes determined by the user. The software has been used in the application to process large image files and identify each plant species for later use. Additionally using the encyclopaedia of arable weeds [2] the software is adapted to identify these hazardous weeds accordingly. Each image is cross referenced over each weed and when there is a high confidence score the image will be flagged.

Bioclip is a preexisting algorithm that outperforms most existing AI tools for detecting plant and animal life. It has a roughly 39.4 % accuracy rating overall and a up to 91.4% average accuracy for plants. While this is already evaluated the variation of the algorithm needs to be examined so our application can use the tool efficiently. When analysing the data used to train the algorithm it is clear that close up images are used so it needs to be evaluated for our application. [1]

The artificial intelligence model is loaded by the application for quick and easy use over large image files. The application will give the user a file containing; Plant species and confidence, if the plant is in the encyclopaedia of arable weeds with its confidence score, GPS location of the plant and its filename. The image path is also included so the user can manually see the image and the visualisation application can display it. A launch button, loading bar and folder selection are added to make the application easy to use. Additionally, the list of arable weeds can be edited to focus on specific plant types or widen the range the classifier will compare against.

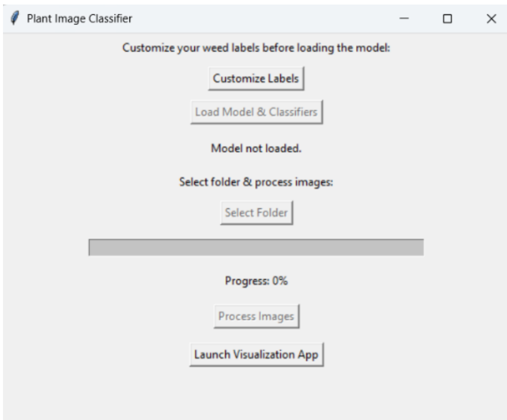


Figure 3 - Plant Classifier GUI


```
{
    "plant_data": [
        {
            "filename": "Image 2 Rododendron.jpg",
            "image_path": "C:\\GitHub\\Proj500\\Proj500\\Test data\\Website Testing\\Image 2 Rododendron.jpg",
            "latitude": 50.37499141,
            "longitude": -4.09397418,
            "custom_predictions": [
                {
                    "classification": "Hawthorn",
                    "confidence": 0.53,
                    "plant_status": "non-harmful"
                }
            ],
            "species_predictions": [
                {
                    "species": "Rhododendron maximum",
                    "confidence": 0.51
                },
                {
                    "species": "Rhododendron haematodes",
                    "confidence": 0.14
                }
            ]
```


Figure 4 - Example File Format Generated by the Plant Classifier Application

6.3 Data Application

The data visualisation Application is a tool used to help display all the data gathered from operation. It was developed using streamlit [19] as a web application and has been customised to make user experience as simple as possible. The two main features are the plant map that shows all the plants identified in the data and the soil data heatmaps. These maps are designed to make it easy for users to identify areas of concern to be able to correct any soil anomalies or remove hazardous weeds. The json file supplied by the system can be uploaded via the sidebar for ease of use.

Each soil reading has its own map which uses the data to determine what colour on the heatmap it will be displayed as. The code adjusts the colour system depending on the data to ensure accuracy and provides an easy visual aid for determining soil anomalies. Additionally hazard threshold for discrepancies between sensors are displayed as hazard symbols to display where sensors could have had issues taking results. The default thresholds have been set using testing data averages of the difference between the two sensors but can be adjusted in the sidebar. Additionally, hovering over the data set will provide the user specific data values from both sensors and the difference between them. All of the data is plotted to its specific GPS coordinates.

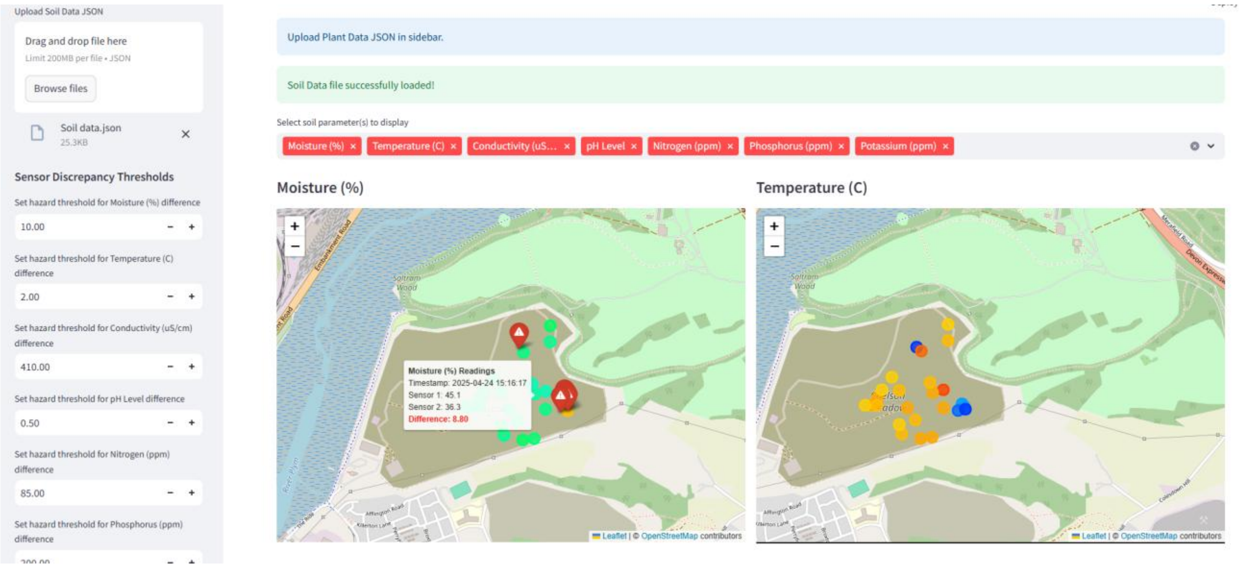


Figure 5 - Soil Data Displayed on Data Visualization Application

The plant map displays all weeds with high confidence as hazard symbols. When hovering over the simple it will display the image in question, along with species, class predictions and confidence scores. The plants not displayed as hazardous are still displayed to provide as much data as possible. In the side bar the plants with lower confidence scores can be filtered out if the user wishes to only see high confidence results. By providing locations and images to the user it makes it as easy as possible for users to locate the harmful plant life.

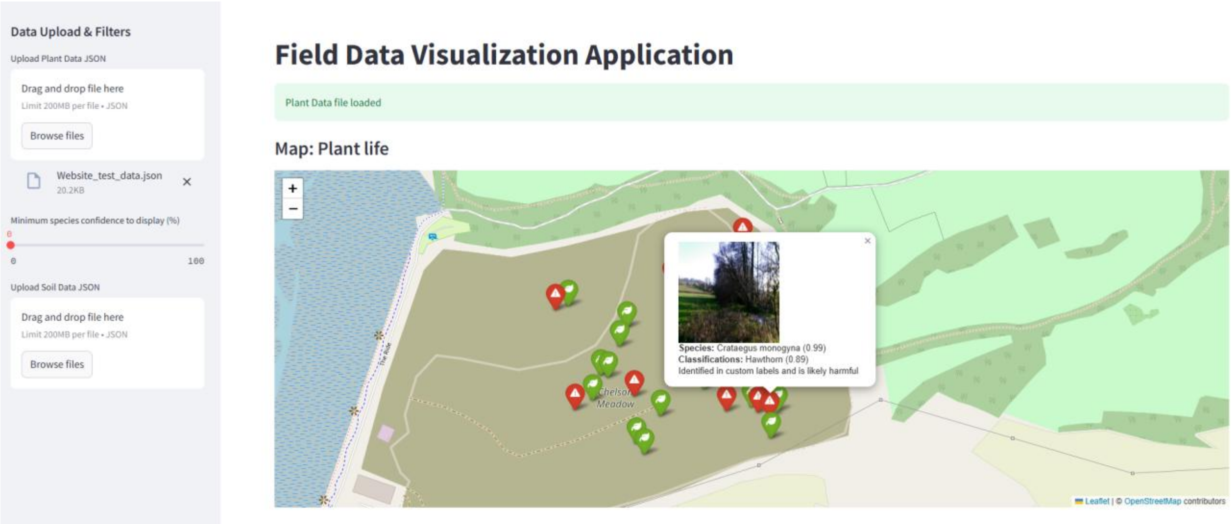


Figure 6 - Plant Data Displayed on Data Visualization Application

6.4 Soil Health System

This section outlines the array of sensors used to gather soil data, the integration strategy to the ASA, and the physical housing design for the sensors that enables the system to collect reliable and actionable soil health metrics in real-time.

6.4.1 Sensor Types

The ASA employs a 7-in-1 soil sensor module that measures:

- Nitrogen (N), Phosphorus (P), Potassium (K) – Essential macronutrients affecting crop yield and plant growth. These elements are the foundation for root development and photosynthesis. Measuring the availability of these nutrients allows targeted fertiliser application to reduce deficiency and nutrient runoff.
- PH – Indicates soil acidity or alkalinity, which is critical for nutrient availability and biological activity. Most crops thrive in a pH between 6.0-7.5, making the monitoring of pH essential to grow specific crops.
- Moisture content – Affects water conservation so that crops are not over-irrigated. Water availability directly impacts plant growth as well.
- Temperature – Influences microbial activity and nutrient solubility as the soil temperature determines the efficiency and rate of microbial processes such as germination and the breakdown and availability of nutrients.
- Electrical Conductivity (EC) – Reflects salinity and overall ion concentration. Higher EC can harm plant roots whereas lower EC may also be a sub-indicator of nutrient deficiency.

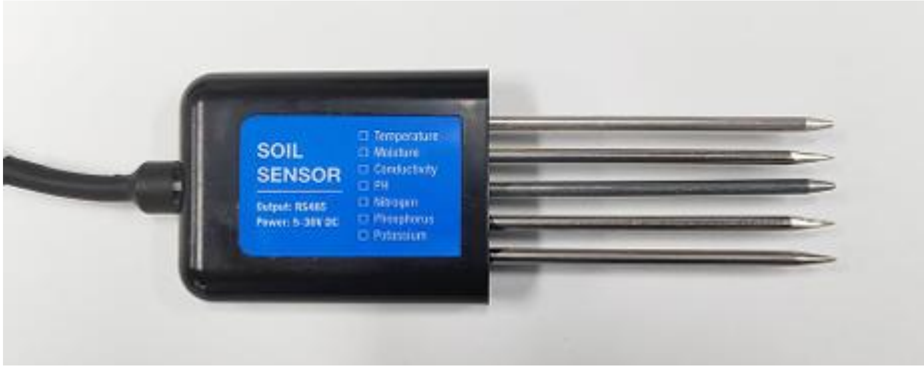


Figure 7 - 7-in-1 Soil Sensor

A combined measurement of all these variables provides farmers with precise real-time data regarding the agricultural land that is monitored. This will allow them to adjust fertiliser and irrigation spread to crops in a variable and more efficient manner to reduce resource wastage, environmental protection, and yield optimisation.

Each sensor output is calibrated and processed into a standard format for logging and geo-tagging, ensuring that there is consistency across readings.

6.4.2 Sensor Integration and Architecture

The sensor module is integrated to the rest of the ASA system via Modbus RTU over RS485, a widely used industrial protocol and physical layer designed for robust, long distance communication with its half-duplex transmission method. Since the GPIO pins on the Pi 5 are allocated to the actuator subsystem, an RS485-to-USB adapter was used to bridge the sensor's serial output to the Pi 5's USB interface.

The benefits of this approach are reduced interference as RS485 supports differential signalling to minimise electromagnetic noise in crucial on-site environments, simplicity and scalability in terms of being able to add several sensors to the single RS485 adapter (in this case, 2 7-in-1 sensors are used in parallel to gather as much data as possible), and overall efficient data polling by allowing structured request and receive queries to the sensor to extract only the required metrics.

Data from the sensor is parsed via Python's serial library by assigning the connected USB port as a dedicated serial port. Data from the sensor is decoded from hexadecimal to decimal values that are readable and printable to both the terminal and a structured JSON file for post-processing.

This modular design separates the sensor system and the control system to allow the ASA to be fault tolerant and more adaptable in use cases. Future versions will be able to change out sensors with more specified or reduced metrics if the same protocol is used for data transfer.

```python
# COM Port Configuration
COM_PORT = "/dev/ttyUSB1"
BAUD_RATE = 4800

# Sensor Device Addresses
SENSOR_1_ID = 0x01  # First sensor address
SENSOR_2_ID = 0x02  # Second sensor address

# Sensor Data Addresses
MOIST = 0x00
TEMP = 0x01
COND = 0x02
PH = 0x03
N = 0x04
P = 0x05
K = 0x06

DATA_CODES = [MOIST, TEMP, COND, PH, N, P, K]
```

Figure 8 - Sensor Initialisation

```python
def poll_all_sensors(ser, sensor_id):
    """Poll all data registers for a given sensor"""
    sensor_data = {
        "GPS": {"latitude": None, "longitude": None}  # Blank GPS fields
    }
    for sensor in DATA_CODES:
        value = poll_sensor(ser, sensor_id, sensor)
        if value is not None:
            labels = {
                TEMP: "Temperature (C)",
                MOIST: "Moisture (%)",
                COND: "Conductivity (uS/cm)",
                PH: "pH Level",
                N: "Nitrogen (ppm)",
                P: "Phosphorus (ppm)",
                K: "Potassium (ppm)"
            }
            label = labels.get(sensor, f"Sensor {sensor}")
            sensor_data[label] = value
        else:
            print(f"Error reading {sensor} from Sensor {sensor_id}")
    return sensor_data
```

Figure 9 - Sensor Polling

```python
def append_results_to_json(sensor1_data, sensor2_data):
    """Append new soil sensor data to a JSON file"""
    try:
        with open("soil_data.json", "r") as json_file:
            data = json.load(json_file)
    except (FileNotFoundError, json.JSONDecodeError):
        data = {"soil_results": []}  # Create new structure if file doesn't exist or is corrupted

    # Append new data entry with timestamp
    new_entry = {
        "timestamp": time.strftime("%Y-%m-%d %H:%M:%S"),
        "sensor_1": sensor1_data,
        "sensor_2": sensor2_data
    }
    data["soil_results"].append(new_entry)

    with open("soil_data.json", "w") as json_file:
        json.dump(data, json_file, indent=4)
```

Figure 10 - JSON File Saving

6.4.3 Sensor Housing

To ensure reliable deployment and repeatable data collection, a custom 3D-printed sensor housing was developed to securely mount the multi-parameter soil sensor. This solution provided a robust and stable platform for the actuators to deploy sensors into the ground, while maintaining precise alignment throughout all testing and field operations.

The sensor housing was designed using Autodesk Fusion 360, enabling precise modelling of dimensions, tolerances, and component integration. This CAD environment allowed for iterative testing of fit and assembly with the actuator arms and surrounding frame, ensuring compatibility with the mechanical system and minimising play or misalignment during operation.

Figure 11 shows the first design which did not work as intended and required parts to be broken off in order to fit the sensors. The parts in the way from Figure 11 were removed and holes were added for sensor cables.

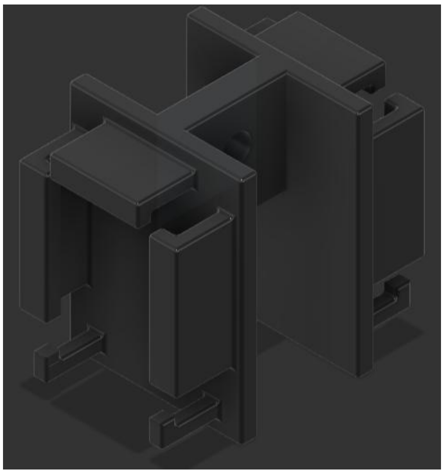


Figure 11 - First design of sensor mount

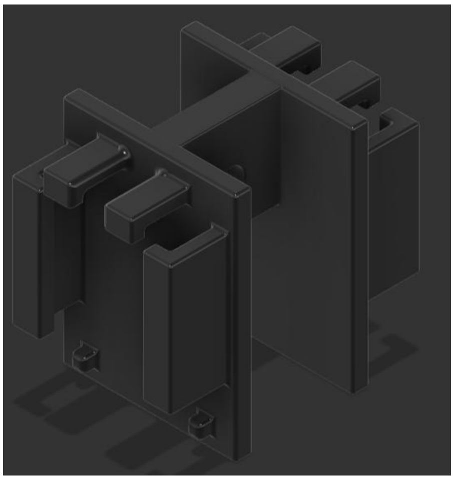


Figure 12 - Second design of sensor mount

The goals of the sensor were or keep the sensors rigidly fixed to the actuator, ensure consistent orientation and depth of the sensors between readings, and allow for easy removal and servicing of individual sensors as they are susceptible to degradation.

The use of 3D printing enabled rapid prototyping and flexibility in design changes. PLA+ filament was used for its improved durability and ease of printing, offering a balance between mechanical strength and print resolution. The printed mount was then mechanically fastened to the actuator arm using bolts and captive nuts to prevent slippage or vibration-induced drift during use.

By maintaining a fixed, reproducible position for each sensor, the mount plays a crucial role in reducing variability in data collection and improving the overall consistency of soil sampling across different test sites.

6.5 Actuator Probing

6.5.1 Actuator Code

The actuator system is controlled through a custom Python script designed to provide flexible, bidirectional control of two linear actuators, one for rock detection and one for soil sensor deployment. The code leverages the lgpio library for low-level GPIO access on the Raspberry Pi 5 and uses PWM signals to drive the actuators via H-bridge motor drivers.

The control logic for the motors lies within motorDriver.py. Upon initialisation, the script claims GPIO outputs for each actuator's direction and enable pins and enables both H-bridge outputs. The actuators are then controlled using dedicated functions as seen in Figure 13

```python
def probeMove(direction):
    if direction == "forward":
        # print("Probe actuator moving forward")
        lgpio.tx_pwm(h, probeRPWM, 1000, 100.0)  # Full power
        lgpio.tx_pwm(h, probeLPWM, 1000, 0.0)  # Off
    elif direction == "backward":
        #print("Probe actuator moving backward")
        lgpio.tx_pwm(h, probeRPWM, 1000, 0.0)  # Off
        lgpio.tx_pwm(h, probeLPWM, 1000, 100.0)  # Full power
    elif direction == "stop":
        #print("Stopping probe actuator")
        lgpio.tx_pwm(h, probeRPWM, 1000, 0.0)
        lgpio.tx_pwm(h, probeLPWM, 1000, 0.0)
    else:
        #print("Invalid argument. Use 'forward' or 'backward'.")
        lgpio.tx_pwm(h, probeRPWM, 1000, 0.0)
        lgpio.tx_pwm(h, probeLPWM, 1000, 0.0)

def testMove(direction):
    if direction == "forward":
        #print("Test actuator moving forward")
        lgpio.tx_pwm(h, testRPWM, 1000, 100.0)  # Full power
        lgpio.tx_pwm(h, testLPWM, 1000, 0.0)  # Off
    elif direction == "backward":
        #print("Test actuator moving backward")
        lgpio.tx_pwm(h, testRPWM, 1000, 0.0)  # Off
        lgpio.tx_pwm(h, testLPWM, 1000, 100.0)  # Full power
    elif direction == "stop":
        #print("Stopping test actuator")
        lgpio.tx_pwm(h, testRPWM, 1000, 0.0)
        lgpio.tx_pwm(h, testLPWM, 1000, 0.0)
    else:
        #print("Invalid argument. Use 'forward' or 'backward'.")
        lgpio.tx_pwm(h, testRPWM, 1000, 0.0)
        lgpio.tx_pwm(h, testLPWM, 1000, 0.0)
```

Figure 13 - snippet of motor driver code.

Each function accepts a string argument ("forward", "backward", or "stop") to determine motion direction. PWM is applied at 1000 Hz with 100% duty cycle for full-speed movement in the selected direction.

6.5.2 Actuator Mounting

A custom actuator mount was developed to ensure the linear actuators were securely and precisely attached to the frame of the ASA platform. Reliable actuator mounting is critical for consistent sensor deployment, as even slight misalignments or instability can affect the accuracy and repeatability of soil probing and could also damage the sensor if a rock or hard soil has not been detected.

The design was iteratively refined to ensure proper alignment with the soil surface and sensor assembly, while also considering the dynamic loads generated during actuator movement and soil penetration.

The final mounts were 3D printed using durable PLA+ material, which provided sufficient mechanical strength for field use while allowing for fast prototyping and low-cost fabrication. These mounts featured precise slots and contours to match the actuator housing profile, a rigid interface with the sensor mount to precent flexing during use.

Each actuator was mounted using heat inserts and M4 bolts, ensuring the units remained firmly fixed to the platform during operation. This mechanical robustness was important for both the obstacle detection actuator and the sensor deployment actuator, as both undergo repeated linear motion with variable resistance due to soil conditions.

By providing a rigid, aligned foundation for the actuators, the custom mounts contributed significantly to the reliability of the soil probing process, minimising lateral movement, reducing measurement error, and supporting long-term deployment of the ASA system in real-world agricultural environments.

6.5.3 Rock Detection

To protect the soil sensors from damage caused by obstacles such as rocks, a rock detection mechanism was implemented using real-time current monitoring of the actuator. This is achieved using the INA219 current sensor, which is interfaced with the Raspberry Pi 5 over the I²C bus. The sensor provides high-resolution measurements of actuator current draw, enabling the system to detect increases in mechanical load.

During the rock detection phase, the designated actuator is commanded to extend into the soil. If the measured current exceeds a predefined threshold, the system interprets this as an encounter with a rock or compacted ground. In response, the actuator is immediately reversed, and the system is repositioned to probe a new location. This cycle can repeat until a safe probing site is identified.

The full actuation sequence is managed in the Autonomous_Soil_Analysis.py script, where the actuator control is integrated with other system processes including sensor polling, camera capture, and data logging. A rolling average filter is applied over a window of 20 current readings to suppress transient noise and improve the reliability of obstacle detection. All current data is also logged to a CSV file so that the data can be used for later analysis.

This software-based detection strategy offers a lightweight and responsive solution for environmental feedback. By dynamically adjusting probing behaviour in response to resistance encountered in the field, the ASA system achieves a higher level of operational safety and reliability, especially in unpredictable soil conditions.

6.6 Overall System Integration

The overall system is centrally controlled by the Raspberry Pi 5 which is powered by the 5V rail on the RTU. The sensors connect to the Pi 5 via a RS485 to USB adapter and the sensors can be powered via the 12V rail from the RTU battery. The camera is connected via a USB port on the Pi 5 as is the external 1TB hard drive. The actuators can be powered by 24V stepped down from the 36V power rail on the RTU and are connected to the Pi 5 via 2 H-bridges for each actuator and the INA219 current sensor. The Pi 5 also has an active cooler with a heatsink attached to it to run just as fast even at higher temperatures and workloads.

All devices mentioned previously are integrated via Python written in Visual Studio Code. The code imports various standard libraries such as serial, sys, time, and OS, but it also adds more hardware specific libraries such as cv2, board and threading. Firstly, the main components and ports are initialised such as the serial port, the motor driver for the H-bridge, sensor IDs and addresses, and a separate thread for the camera.

The main loop of the code establishes a serial connection before starting the actuator to probe the ground. If a rock is detected, the system will move to another location until an area without a rock or firm ground is detected. This will then allow the system to move so that the actuator with the sensors is at the same point so that soil can be collected. The sensors require 1 minute to stabilise before the readings are confirmed to be accurate according to the sensor datasheet. Multiple readings can be taken at this point based on user requirements and appended to the JSON file before the sensor actuator is removed from the ground and the entire process repeats again until the whole field has been evaluated. During this data collection process, the camera thread is constantly taking pictures of the environment and saving to the removable hard drive at a predetermined rate of every 10 seconds (can be adjusted by the user according to their needs).

After monitoring the entire agricultural area, the hard drive can be removed and post-processed on a laptop or desktop computer as described in parts 6.2 and 6.3 for plant identification and data visualisation.

7 Development and Testing

7.1 Camera

7.1.1 Camera angle

To evaluate the camera's performance under various conditions, a series of tests were conducted to determine the optimal positioning and environmental setup. This process involved capturing images of plants, weeds and hedgerows in different conditions and angles. Each image was processed through the classification algorithm, and the resulting confidence scores were analysed. By manually verifying the classifier's outputs, optimal positions corresponding to higher confidence scores were identified.

Testing was conducted under two conditions: one where the camera's height and distance remained constant, and a second where the camera angle was varied while adjusting the height to maintain the plant at the centre of the frame. These tests aimed to determine the optimal setup conditions for achieving high confidence scores and to provide insight into how the setup could be optimised for the algorithm. The first test shows Hawthorn in a field, mimicking the setup the RTU would experience in operation. The second test saw a more controlled environment focusing on identifying plants and conditions yield the highest confidence scores. It is important to conduct controlled and operational testing to identify not just optimal setup, but also any factors in operation that may influence the final decided setup.

Figure 15 - Field - Hawthorn

Figure 14 - Controlled - Rhododendron

Table 2 shows that confidence scores are higher when the plant is positioned lower in the frame. This suggests that having other vegetation in the shot lowers the confidence, so focusing on individual plants gives better results. The focus points of the camera appear to influence the confidence scores more significantly than the angle. When analysing the data, it becomes evident that even if the hawthorn occupies a large portion of the image, poor focus, or focusing on a smaller section of the image, causes the confidence scores to drop dramatically. Positioning the hawthorn lower in the frame helps the camera to focus more effectively and reduces the influence of surrounding features on the scores.

When providing the algorithm, a class item of just Hawthorn each entry would be 100% confident. With each item added or the full list of arable weeds the confidence fluctuates. This will be discussed further in section Plant Classifier.

Table 2 - Data for Angle Testing - Hawthorn

Camera Angle test 1				
Returned Result Type			Species	
Species:			Plantae Tracheophyta Magnoliopsida (Hawthorn)	
			Angle	Confidence
Parameters			60	>5
			65	>5
Distance	2M		70	>5
Height	1.5M		75	>5
			80	54
Distance and height remain constant			85	99
			90	82
			95	70
			100	Out of range

For Test two, in the controlled environment the rhododendrons were photographed at varying angles but keeping the centre of focus on the plant. Seen in Table 3 the results suggest that when the flowers are in main focus the confidence scores are higher. The results are what was expected due to the main identifier being the colour and leaf shape of the plant. Additionally, it shows that focus on the plant is more important than angle due to the average confidence being higher in Table 2 than Table 3. It is shown in the data that the lower maximum score may be due to there being multiple species of rhododendron as opposed to hawthorn affecting the overall confidence scores. The photos were cropped to ensure as little external factors as possible affected the score.

Table 3 - Data for Angle Testing - Rhododendron (cropped)

Camera Angle test 2 (Cropped Images)				
			Species: Rhodedendron	
			Angle	Confidence
Parameters			90	12
			85	29
Distance	0.5M		80	37
Height	Varied to keep flower centre of frame		75	63
			70	67
			65	67

Overall, the Camera angle when looking at plants does not appear to be the biggest contributing factor to reliability of the system. Other contributing factors discussed in the report such as focus; background and picture quality seem to be more important. However, when conducting the test, it does appear that focusing on flowers shape and colour increases confidence. Therefore, regardless of other factors a higher angle facing down appears to aid in reliability.

7.1.2 Picture Quality

Field testing was conducted in diverse environments, including Dartmoor and an agricultural field. During these trials, it was observed that the camera's autofocus system performed less effectively when there was minimal background detail or when the subject lacked nearby contextual features. As shown in, Figure 16 and Figure 17, two images taken from slightly different angles, with no background activity displaying the image quality. The cameras autofocus performed optimally when the primary subject was within ten meters and when background elements were present to assist with depth perception. However, it was still capable of functioning at greater distances when some background structure was available.

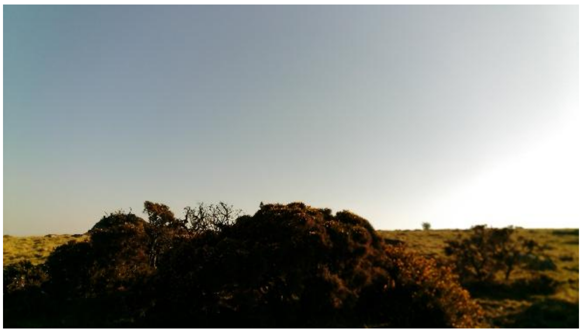


Figure 17 - Clear Image at 100º with Little Background Activity

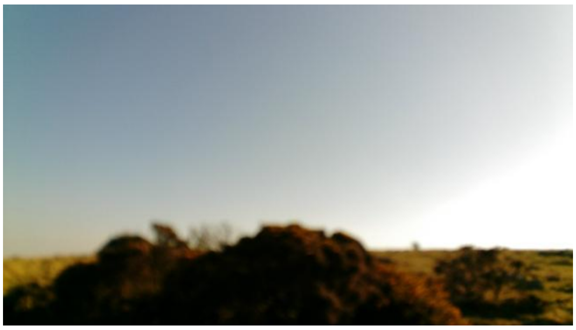


Figure 16 - Blurry Image at 110 º with Little Background Activity

Additional testing was conducted under varying lighting conditions. The camera consistently adapted well, even in shaded environments, as shown in Figure 18 and Figure 19. It automatically adjusted exposure to maintain image clarity. Additionally, the confidence scores of two images at the same angle with different lighting conditions only differed by 12%. The scores were gathered using the class option when all arable weeds were entered.

Figure 18 - Shaded Area Image Quality

Figure 19 - Lightened Are Image Quality

However, the system showed limitations when exposed to intense direct sunlight, particularly when lens flare occurred. When the camera caught the sun the colour saturation would change leading to a confidence change of 0.5 seen in Figure 22. The first image despite looking like it is more vibrant doesn't capture the plant in as much detail leading to the confidence reduction, shown in Figure 20 and Figure 21.

Figure 20 - Image WIN20250410 17_49_27

Figure 21 - Image WIN20250410 17_49_23

```json
    {
        "filename": "WIN_20250410_17_49_23_Pro.jpg",
        "species_predictions": [
            {
                "species": "Ulex europaeus",
                "confidence": 0.88
            }
        ]
    },
    {
        "filename": "WIN_20250410_17_49_27_Pro.jpg",
        "species_predictions": [
            {
                "species": "Ulex europaeus",
                "confidence": 0.38
            }
        ]
```


Figure 22 - Image Quality Confidence Scores

7.1.3 Camera Testing Conclusion

The testing suggest that the camera performs well under the conditions it will be subject to in the field. Plant identification scores do offer consistency in results and the autofocus works when set up at an angle within 60 to 90 degrees. The camera struggles with little background activity to focus so a lower than 90-degree angle is crucial. This is supported by the results gained in Table 3 which shows that when in a controlled environment a lower angle is best. In contrast Table 2 shows that when in a more realistic environment shows a higher angle close to ninety decreases the surrounding activity focusing on the hawthorn. Overall, the data suggest that for best results an 80–85-degree angle should be used to maintain focus on the plant/weeds. Likewise, the angle provides more coverage of the landscape whilst continuing to focus on specific anomalies.

7.2 Plant Classifier

The plant classification system used in the application relies on two key features that must be tested for accuracy to ensure the reliability of the app. First, the classifier must output results with sufficient confidence. Second, it should provide results mapped to commonly used plant names to enhance user accessibility. The classifier determines the plant species by identifying the genus using scientific nomenclature.

To evaluate the classifier's performance, images of known plant species were captured and manually verified for accuracy. A wide variety of images were taken across different environments and conditions to assess classification robustness. Table 4 Shows that the classifier performs well predicting all twenty plant types with only three occasions the top answer was not correct. On average the confidence scores were 53.2% showing that there is still room for improvement. However, thee range of confidence scores is eighty-five showing there is a low consistency for confidence.

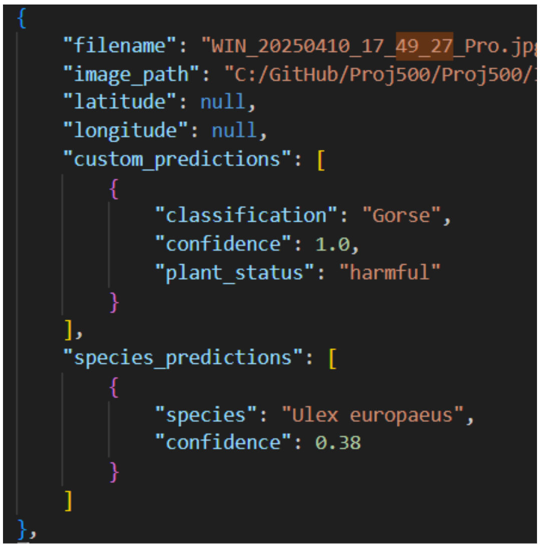
When analysing the results it became clear that when a particular species has many sub species, for example Yew, the confidence scores lower dramatically to around twenty compared to plants with less sub species. In this testing a varied range of environments were used and entries 15 to 20 proved the classifier can deal with it well. These images offered more background and surrounding features made to test the classifier. Each image the clarifier correctly identified with a high average in confidence score. With this testing done limits as to what is displayed in the data visualisation app can be set to prevent misleading or missing information. A preliminary score of above 50% or the maximum value above 20% if not values exceed fifty. Additionally, bellow 20% would be considered uncertain. These limits help identify plant life while removing misleading results.

Table 4 - Species Classifier Testing

Bioclip Testing

Image Number	Identified Species/Type	Bioclip Result	Percentage (%)	Species Correct?	Notes
1	Mixture of items likely English ivy	Euonymus fortunei 36% (Winter Creeper) Hedera iberica 26% Hedera helix 21% (English Ivy)	21	Y	Mixture of Species likely English ivy but other prediction pictures match image
2	Rododendron	Rododendron Maximum	51	Y	
3	Gorse	Ulex europaeus (common gorse)	38	Y	
4	Beales Barberry	Berberis bealei	74	Y	
5	Hedge Parsley	Torilis japonica	28	Y	
6	Holly	Ilex colchica 44% (Black Sea Holly) Ilex aquifolium 43% (English Holly)	43	Y	2nd Option
7	Yew	Taxus contorta 30% (West Himalayan Yew) Tsuga chinensis 26% (Chinese Hemlock) Taxus baccata 14% (English Yew)	14	Y	3rd option
8	Hawthorn	Crataegus monogyna (Hawthorn)	70	Y	
9	Garlic Mustard	Alliaria Petiolata (Garlic Mustard)	77	Y	
10	Ragwort	Jacobaea vulgaris (Ragwort)	54	Y	
11	Hedge Musaterd	Sisiymbrium officinale (Hedge Mustard)	55	Y	
12	Oil Seed Rape	Brassica napus (Rape)	96	Y	
13	Charlock	Sinapis arvensis (Charlock) 52% Rapistrum rugosum 40%	52	Y	
14	Bur Chervil	Anthriscus sylvestris (Bur Chervil)	82	Y	
15	Field sow thistle	Sonchus arvensis (Field sow thistle)	54	Y	
16	Ragwort	Jacobaea vulgaris (Ragwort)	25	Y	
17	Meadow Brome	Bromus erectus (20%) (Meadow Brome)	20	Y	
18	Heather	Calluna vulgaris (Heather)	99	Y	
19	Meadow Bistort	Bistorta officinalis (Meadow Bistort)	95	Y	
20	European Yellow Lupine	Thermopsis chinensis 27% Lupinus luteus 15% (European Yellow Lupine)	15	Y	Flowers almost identical
		Average	53.2		
		Range	85		

When classifying plants using broader categories or classes (Appendix A – Arable weeds for classification), the model showed a higher likelihood of successful identification. However, if a particular plant type was not included in the predefined list, the algorithm tended to assign a best-fit label rather than identifying the actual species. Figure 23 and Figure 24 illustrates an example of this behaviour, showing the same image classified differently depending on whether the species was included in the class list. With this in mind a high confidence threshold is needed when displaying class items and what is determined as harmful or not. Setting classifier at a high confidence threshold of 80%, means the algorithm has to be sure the plant species is in the class list to label it as harmful. Then only class entries above 50% will be shown in the application but as non-harmful if below 80%.



```
{
    "filename": "WIN_20250410_17_49_27_Pro.jp
    "image_path": "C:/GitHub/Proj500/Proj500/i
    "latitude": null,
    "longitude": null,
    "custom_predictions": [
        {
            "classification": "Gorse",
            "confidence": 1.0,
            "plant_status": "harmful"
        }
    ],
    "species_predictions": [
        {
            "species": "Ulex europaeus",
            "confidence": 0.38
        }
    ]
},
```

Figure 24 - Class Classification when Gorse Added

```
{
    "filename": "WIN_20250410_17_49_27_Pro.jpg",
    "image_path": "C:/GitHub/Proj500/Proj500/Images
    "latitude": null,
    "longitude": null,
    "custom_predictions": [
        {
            "classification": "Sunflower",
            "confidence": 0.47,
            "plant_status": "non-harmful"
        },
        {
            "classification": "Scented mayweed",
            "confidence": 0.32,
            "plant_status": "non-harmful"
        }
    ],
    "species_predictions": [
        {
            "species": "Ulex europaeus",
            "confidence": 0.38
        }
    ]
},
```

Figure 23 - Class Classification Before Gorse Added

Lastly the images supplied come with EXIF data encoded into the image that the control system supplies. The encoded data is extracted using a set of functions that is then converted to GPS data and written to the JSON file. This GPS location will then be shown on the application shown in Figure 5 and Figure 6.

7.3 Data Visualisation Application

Each feature mentioned in 6.3 needed to be tested for function. The heat spots code was developed to average out the data and develop a faded scale for visual representation. This can be seen in image Figure 5 with the data showing the temperature variation. Likewise, each sensor reading and sensor difference can be checked by hovering over the data set. Each threshold can be adjusted and the map updates to show hazard symbols where the difference lies outside the bounds.

Similarly to the soil maps the plant map was checked to ensure each image was displayed correctly and each hazard was displayed as intended. Additionally, the confidence scale on the side bar is adjusted to see the lower confidence scores be hidden as seen in Figure 25 and Figure 6.

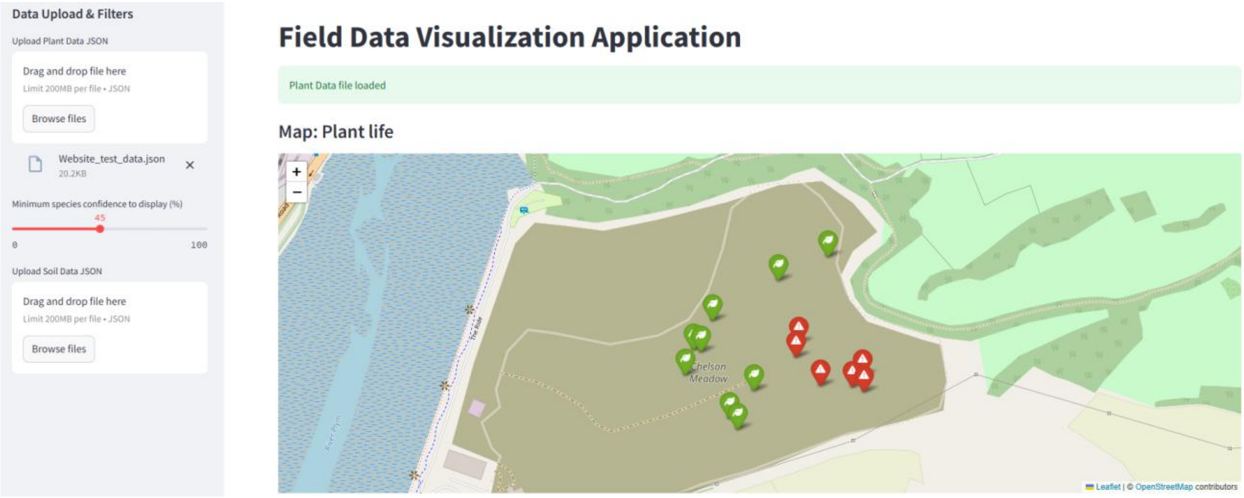


Figure 25 - Plant Map with 45%+ Confidence.

7.4 Sensor Testing

The accuracy and reliability of the soil sensors are critical for ensuring that the ASA system provides meaningful, actionable data to support agricultural decision-making. This section evaluates the performance of the integrated 7-in-1 soil sensor module through individual testing of each parameter: moisture, temperature, electrical conductivity, pH, nitrogen, phosphorus, and potassium. Testing was conducted under both controlled and field conditions where appropriate, using reference instruments and different soil samples to assess sensor accuracy and consistency. The following subsections detail the methodology, results, and implications of each sensor's performance, highlighting any limitations and justifying the sensor's inclusion in the final system architecture.

All sensors were initialised according to the datasheet spec. This process involved running an application on the datasheet website to zero/calibrate all the sensors.

The calibration for moisture was verified by submerging the sensor probes at various depths of water. In air a 0% reading would be achieved, whereas a 100% reading would be logged when fully submerged. The moisture reading is representative of total probe surface area covered which is the same as the other metrics.

A similar calibration was performed for temperature. Based on correlating the reading of the sensor to a thermometer in the test area at room temperature seemed to show that the reading was ±0.5°C off from the thermometer as detailed in the specification document. It was also verified that the temperature reading would fluctuate expectedly as the probe was placed within colder areas such as a fridge or warm water.

Calibration tests for the other measurements could not be fully verified without soil testing but all of which read zero when monitoring the air as expected.

All following tests were carried out across four soil types: A-Soft Soil, B-Stony Soil, C-Compost, and D-Grow Kit. All the tests were conducted in a controlled indoor environment using soils A, B, C and D in a planting pot of one litre in volume filled with the specified soil. For each test, the sensors are inserted to a depth of 8cm to ensure that the probes are fully immersed in the soil. For each independent data point, three measurements are made to calculate the average measurement as well as the standard deviation. These values are plotted on the graphs later in this section.

7.4.1 Moisture Testing

The objective of this test was to evaluate the moisture sensor's accuracy and responsiveness in detecting moisture content in soil.

The methodology for this test was to measure the sensor values for each soil type in a controlled environment. After each measurement, 5ml of water was added to the soil sample and left to settle for 1 minute to spread evenly in the soil. The sensor would then be probed into the soil again for each 5ml increment up to 200ml for each soil type. The values at each increment are then averaged and the standard deviation between them is calculated and plotted as seen in Figure 26 below.

Across all measurements, the sensor results showed the expected trend of moisture content increasing as water is added to the soil. The error margins for these measurements were greatest during the earlier increments as the water added did not have time to settle in the soil potentially causing varying measurements in the sensor due to inconsistent moisture contact with the probe.

Soil A, the soft soil, has a rapid moisture increase as water is added until 100ml and then starts plateauing. The saturation point of this soil is around 100-120ml with average moisture content between 73-74%. This indicates that the soil has a high-water uptake capacity due to being a very small particulate soil which is the expected result.

Soil B, the stony soil, has a slower and steadier moisture increase as water is added until 60ml and then begins to level off. The saturation point of this soil is around 65-70ml where the moisture content stabilises around 65-66%. This shows that the soil has moderate water retention due to having stones within the soil. This is expected as more porous stony soil tends to be used to drain water rather than hold it.

Soil C, the compost, has a gradual continuous increase in moisture content across the full water range with no strong plateau. A saturation is not clearly reached by the 195ml mark with a moisture content of 88-89%. This shows that the compost has a high capacity for water absorption, with a slow and steady uptake, due to fine texture and due to being composed of more than just soil with absorbative sediment as well within it. The error margins for this soil seem to also continue throughout due to the lack of a plateau.

Soil D, the grow kit, has a very high initial moisture content at 84% due to needing water to turn it from a dry brick of sediment into usable soil. As water is added, the soil seems to already be quite saturated with minimal increase in moisture content as it reaches 96% at its peak. This is due to the initial soil being quite muddy already with poor drainage and high moisture retention meaning that additional water has marginal impact as is expected.

These results demonstrate that the moisture sensor can detect and reflecting distinct moisture absorption behaviours across different soil types. The consistent trends and identifiable saturation points support the sensor's responsiveness, while the observed standard deviations highlight areas (such as early increments or unevenly structured soils) where contact variability can influence accuracy.

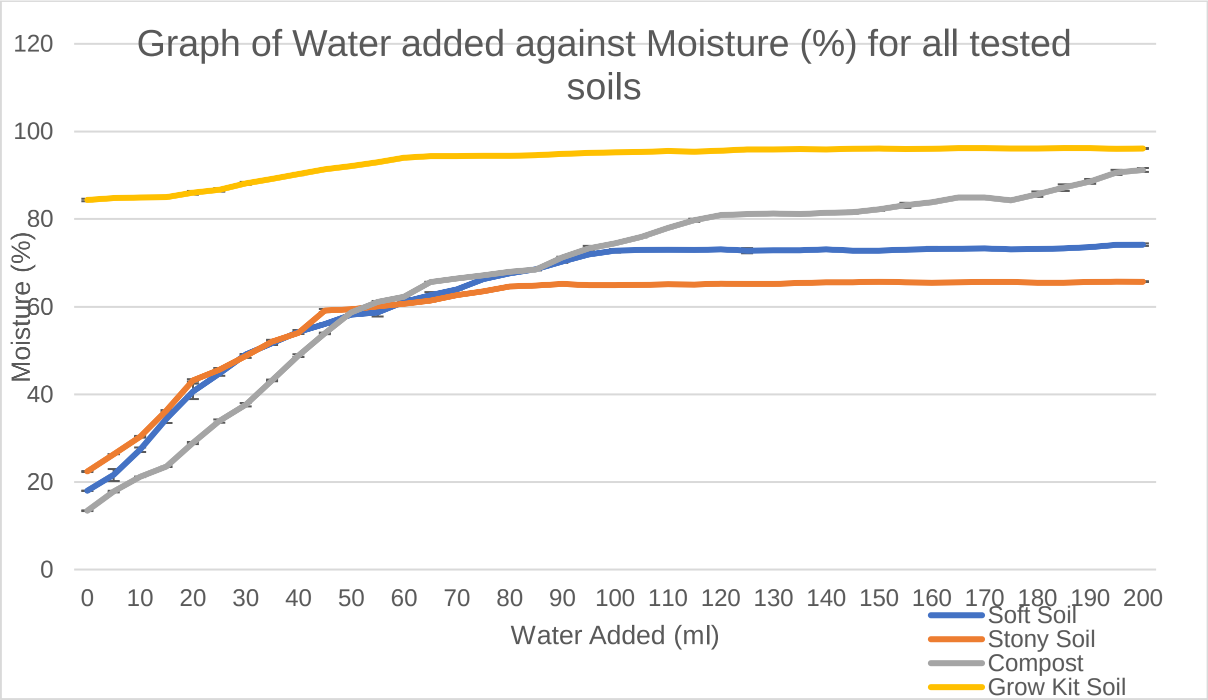


Figure 26: Graph of Water added against Moisture (%) for all tested soils.

7.4.2 Temperature Testing

The objective of this test was to evaluate the temperature sensor's accuracy and consistency in measuring temperature across different soil types and in the surrounding air.

The methodology involved measuring the temperature using both a sensor and a thermocouple at three distinct points for each soil type, and for the air, under controlled conditions. The temperature measurements were then averaged and the standard deviation calculated to assess consistency.

Across all measurements, both the sensor and thermocouple showed very similar trends and values. The sensor readings typically exhibited a slightly lower average temperature compared to the thermocouple, but the differences were minimal.

For Soil A (soft soil), both the sensor (21.83°C) and thermocouple (22.13°C) showed near identical average temperatures with low variability (Std Dev ~0.06°C), indicating similar performance in stable conditions.

In Soil B (stony soil), the sensor recorded 22.53°C, while the thermocouple was slightly higher at 22.93°C, consistent with its tendency to overestimate in the presence of heat conducting particles like stones. Both methods had low variability, but the thermocouple readings were marginally higher.

For Soil C (compost), both the sensor (23.23°C) and thermocouple (24.03°C) exhibited stable readings with very low variability (Std Dev ~0.06°C), indicating consistent temperature measurement across this soil type.

Soil D (grow kit) showed a greater disparity, with the sensor reading 21.37°C and the thermocouple at 22.47°C. The sensor’s higher variability (Std Dev 0.23°C) suggests more fluctuation in temperature, likely due to the soil's texture or composition. In contrast, the thermocouple provided more stable readings.

In the Air measurements, the sensor recorded 22.43°C, and the thermocouple measured 24.3°C, with both methods showing very low variability (Std Dev ~0.06°C for the sensor and 0.1°C for the thermocouple), but again, the thermocouple registered a higher temperature.

These results suggest that both the sensor and thermocouple provide reliable and consistent temperature readings across different soil types, with only slight differences between the two measurement methods. However, the higher standard deviation observed in Soil D indicates that the grow kit may have more heterogeneous thermal properties, which could affect the sensor's ability to consistently measure temperature in such soils. Overall, this sensor seems suitable for use in measuring temperature for the ASA.

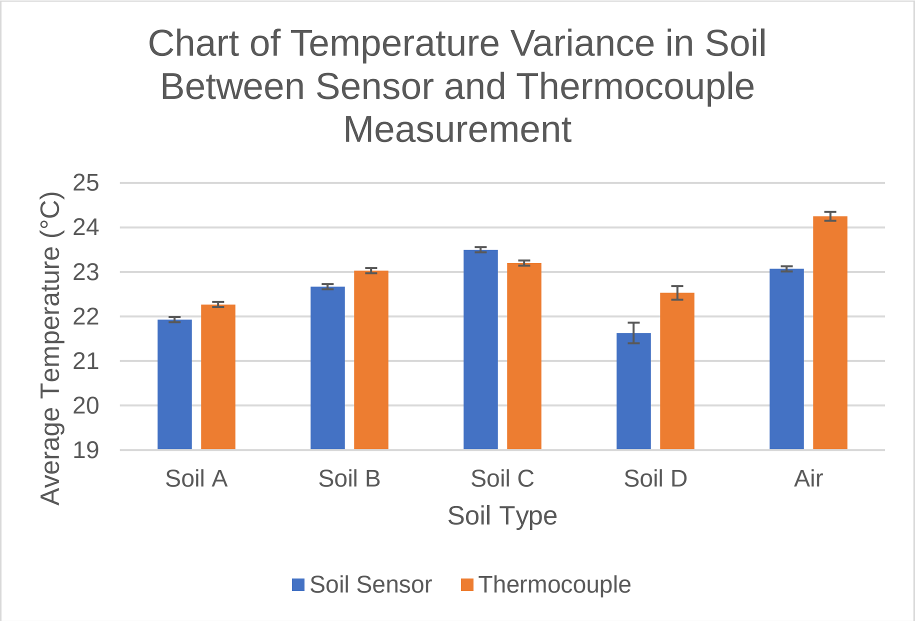


Figure 27: Chart of Temperature Variance in Soil Between Sensor and Thermocouple Measurement

7.4.3 Electrical Conductivity (EC) Testing

Comparative testing could not be done for EC as a standard EC testing kit could not be found in time. However, a higher EC measurement is indicative of higher NPK values due to the higher ion availability.

The methodology for this test was to take three measurements in each soil to calculate an average and a standard deviation.

Soil A (Soft Soil): Conductivity was consistent at 146 µS/cm for all measurements, showing no variability (Std Dev = 0). This indicates a stable conductivity level, suggesting moderate ion availability but unlikely to influence ASA suitability significantly.

Soil B (Stony Soil): Similar consistency with an average of 158 µS/cm, no variability (Std Dev = 0). The conductivity is moderate, indicating potential for ion exchange without notable changes.

Soil C (Compost): Measurements averaged 141.67 µS/cm, with very slight variability (Std Dev = 0.58). The slight variability still shows consistency.

Soil D (Grow Kit): Conductivity averaged a high 1358 µS/cm, with minimal variability (Std Dev = 1.73). This indicates very high ion availability.

Due to the lack of a comparative measurement, the EC sensor's suitability for use with the ASA cannot be fully evaluated without further testing, however it is consistent with the NPK results that are shown later in this section as a cross-reference data point in terms of accuracy.

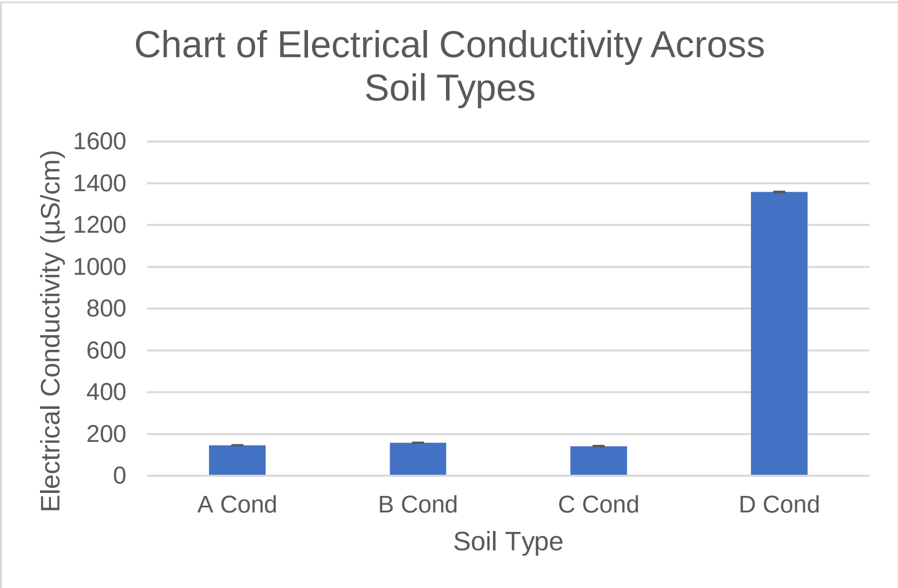


Figure 28: Chart of Electrical Conductivity Across Soil Types

7.4.4 PH Testing

The objective of this test was to assess the accuracy and consistency of both the sensor and test kit in measuring the pH levels across different soil types.

The methodology involved measuring the pH of each soil type using both a sensor and a lab test kit. The readings were taken three times for each method and soil type, and the average pH value was calculated. The standard deviation was also computed to evaluate the variability of the measurements.

Across all measurements, the sensor and test kit showed some differences in their pH readings, but both methods generally exhibited low variability within each soil type.

Soil A (soft soil) showed a consistent pH of 6.73 with the sensor (Std Dev 0.058), while the test kit recorded a higher, consistent pH of 8. Soil B (stony soil) had a stable sensor reading of 7.1 (no variability), compared to the test kit's higher pH of 9. In Soil C (compost), the sensor showed more variability (average 6.97, Std Dev 0.493), while the test kit gave a higher average of 8.67 with slight inconsistency. Soil D (grow kit) had a consistent pH of 6.1 from the sensor, but the test kit measured a higher average of 7.33 with more variability. Overall, the test kit consistently recorded higher pH values than the sensor across all soil types, with the sensor showing greater variability in more complex soils like compost.

In conclusion, while both the sensor and test kit provided consistent measurements within each soil type, the test kit generally yielded higher pH values, suggesting it may be more sensitive to certain soil compositions. The Autonomous Soil Analyser (ASA), using the sensor, offers real-time, direct pH readings with low variability, making it suitable for continuous monitoring in agricultural environments. However, its accuracy may be influenced by soil complexity, as seen in more heterogeneous soils like compost. The test kit, while precise in its discrete colour-based readings, may offer less flexibility for real-time analysis compared to the pH sensor. Therefore, for ongoing pH monitoring, the ASA's sensor provides a practical and consistent solution, although calibration adjustments may be needed for certain soil types.

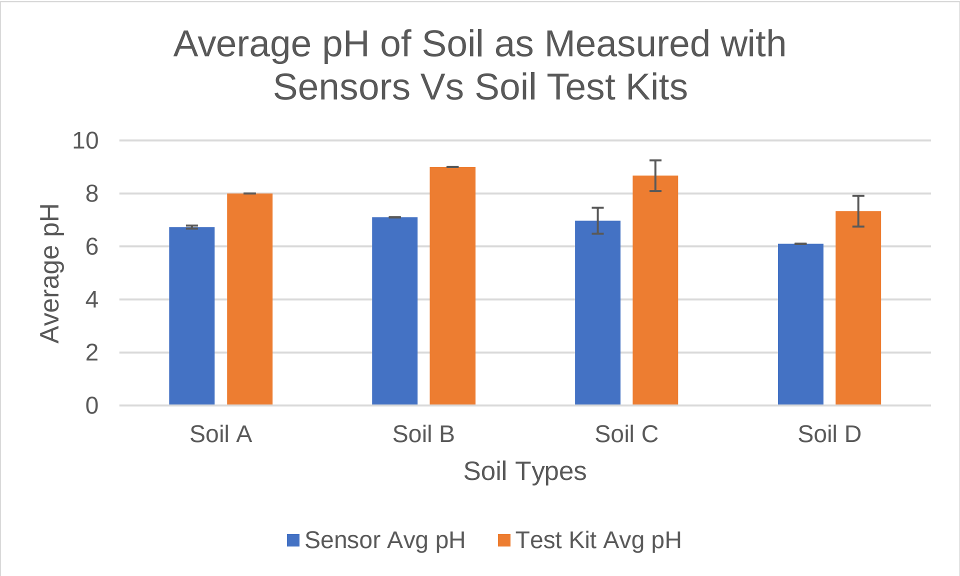


Figure 29: Average pH of Soil as Measured with Sensors Vs Soil Test Kits

7.4.5 Nitrogen Testing

The objective of this test was to evaluate the accuracy and consistency of the nitrogen (N) readings from both the sensor and chemical test kit across a range of soil types with varying nutrient levels.

Soil A, B, and C all demonstrated extremely low nitrogen levels according to the sensor, consistently returning values of 0 ppm across all three measurements. This indicates a clear detection of nutrient-poor conditions, with no variability (Std Dev = 0). The test kit, however, recorded values of 10 ppm for Soil A, a highly inconsistent mix of 0 and 10 ppm for Soil B (average= 6.67 ppm, Std Dev = 5.77), and primarily 0 ppm for Soil C (average = 3.33 ppm, Std Dev = 5.77). The variation in the test kit results, especially for B and C, likely reflects either borderline detection levels or interpretive differences from the colour-based method.

In contrast, Soil D which is known to be nutrient-rich, produced dramatically higher readings. The sensor returned consistent nitrogen values averaging 269.3 ppm with very low variability (Std Dev = 3.21), clearly distinguishing it from the nutrient-poor soils. The test kit, while correctly indicating high nitrogen levels, varied significantly between 200 and 500 ppm (average = 300 ppm, Std Dev = 173.2), highlighting potential subjectivity or sensitivity limitations in visual colour comparison.

In conclusion the nitrogen sensor effectively distinguished between nutrient-poor and nutrient-rich soils with high consistency and precision, making it highly suitable for agricultural applications where reliable nutrient monitoring is essential. Compared to the chemical test kit uses a colorimetric scale to estimate nitrogen levels, where users visually match the soil solution’s colour to a reference chart. This scale includes distinct colours corresponding to fixed nitrogen values: bright yellow for 0 ppm, neon yellow for 10 ppm, greenish yellow for 50 ppm, lime for 100 ppm, green for 200 ppm, and dark green for 500 ppm. While this provides a quick, low-cost estimation method, it introduces subjectivity and limits precision particularly in borderline cases or when colours are difficult to differentiate under varying lighting. This was evident in the inconsistent readings for Soils B and C, where slight shifts in hue may have led to different interpretations.

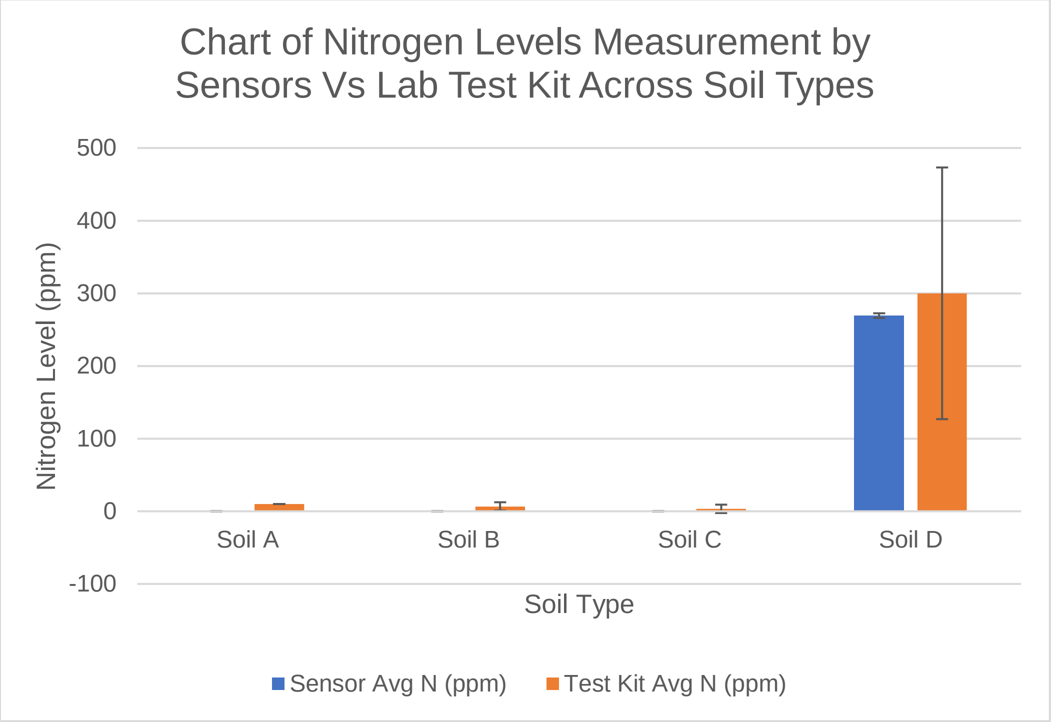


Figure 30: Chart of Nitrogen Level Measurement by Sensors Vs Lab Test Kit Across Soil Types

7.4.6 Phosphorus Testing

This phosphorus test aimed to evaluate the accuracy and consistency of both the phosphorus sensor in the 7-in-1 soil sensor and the chemical test kit across four soil types, with a focus on the sensor's suitability for use in the Autonomous Soil Analyser (ASA).

Soils A, B, and C all exhibited low phosphorus content according to the sensor, with values ranging from 27–33 ppm. These readings were consistent across all three measurements for Soils A and B (Std Dev = 0), indicating high precision. Soil C showed slightly more variability (average = 27 ppm, Std Dev = 3.46), likely due to soil texture or inconsistencies in sampling. In comparison, the test kit reported more variable and often inflated values for these soils. Soil A's test kit results ranged from 20 to 50 ppm (average = 30 ppm, Std Dev = 17.32), while Soil C ranged from 20 to 50 ppm (average = 40 ppm, Std Dev = 17.32), suggesting inconsistent interpretation of the colour scale. Notably, Soil B had consistent test kit results (20 ppm, Std Dev = 0), matching the lower range detected by the sensor.

Soil D, which again proved to be the most nutrient-rich sample, showed a significantly higher phosphorus content with the sensor averaging 669 ppm and a low variability (Std Dev = 7.81), indicating a reliable and strong phosphorus presence. However, the test kit reported values between 120 and 240 ppm (average = 200 ppm, Std Dev = 69.28), substantially underestimating the actual concentration and showing high inconsistency.

The chemical test kit's colour scale used for phosphorus relies on visual matching of soil extract colours to fixed value references: light yellow (0 ppm), yellow (20 ppm), pale skin colour (50 ppm), beige (80 ppm), pink (120 ppm), and purple (240 ppm). This approach introduces significant subjectivity and inaccuracy, especially when intermediate colours are hard to distinguish or overlap under varying lighting. This was evident in Soils A and C, where sensor data suggested stable phosphorus content, but the test kit produced inconsistent or overestimated results.

In summary, the phosphorus sensor provides clear advantages in precision, consistency, and objectivity over the colorimetric test kit. This makes it more suitable for accurate nutrient analysis in agricultural environments, particularly where nutrient levels vary widely or frequent, automated monitoring is required.

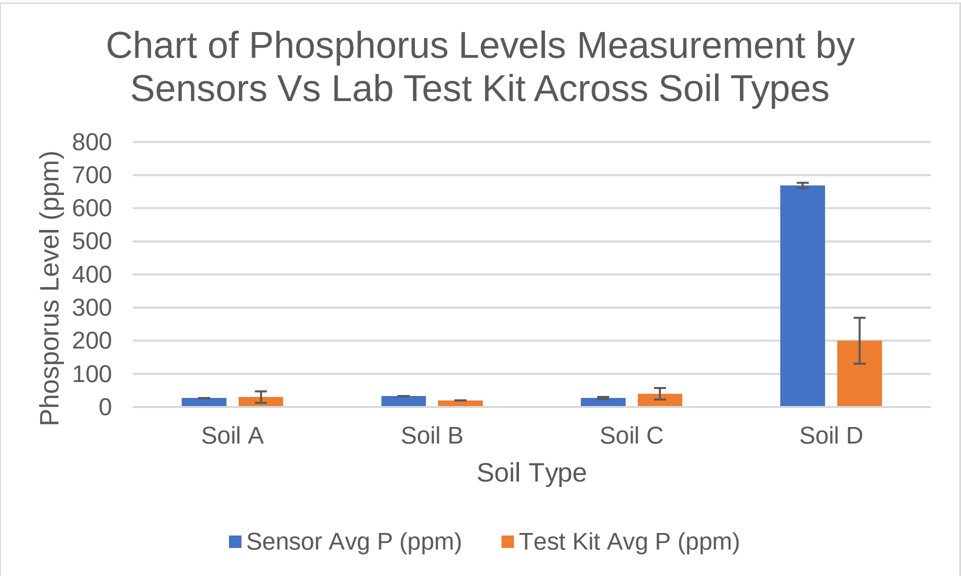


Figure 31: Chart of Phosphorus Level Measurements by Sensors Vs Lab Test Kit Across Soil Types

7.4.7 Potassium Testing

This test aimed to evaluate the performance of the potassium (K) sensing capability of the 7-in-1 soil sensor by comparing its measurements to a commercially available chemical soil test kit across 4 soil types with a focus on the sensor's suitability for use in the Autonomous Soil Analyser (ASA).

Four soil samples with varying potassium levels were tested. Each sample underwent three repeated measurements from both the digital sensor and the chemical test kit. The colour chart provided by the kit was used to derive approximate potassium values in ppm based on visual identification: Dark yellow = 0ppm, Light yellow = 20ppm, Gold = 50ppm, Brass 80ppm, Greyish Brown = 120ppm, and Grey = 240ppm.

Across samples A–C, the potassium sensor demonstrated good agreement with the chemical test kit, with average readings generally within ±5 ppm of the visual kit estimates. While some variability was observed particularly in Soil B due to one anomalously low reading, the standard deviations remained within acceptable limits for in-field measurements. This suggests the sensor is sufficiently reliable for identifying relative differences in potassium content among low to moderate fertility soils.

In contrast, Soil D, which is known to be significantly more nutrient-rich, revealed a notable discrepancy between the sensor and the chemical test kit. The sensor reported values exceeding 660 ppm, whereas the kit indicated an average of 160 ppm. The chemical kit relies on discrete, colour-based ppm thresholds (e.g., 0, 20, 50, 80, 120, 240 ppm), which introduces quantisation error and makes it difficult to interpolate intermediate values accurately. This stepwise resolution likely contributes to the underreporting of potassium in highly enriched samples like Soil D.

While the potassium sensor proves effective for distinguishing soil fertility in the lower ranges, its performance at higher concentrations may require calibration against known standards to correct for potential overestimation. Additionally, the comparison highlights the limitations of visual test kits in providing precise quantitative data, especially in the context of high-resolution sensor outputs. For the ASA system, the potassium sensor is suitable for real-time field assessments and soil condition monitoring, though further refinement may improve its accuracy across the full spectrum of soil nutrient conditions.

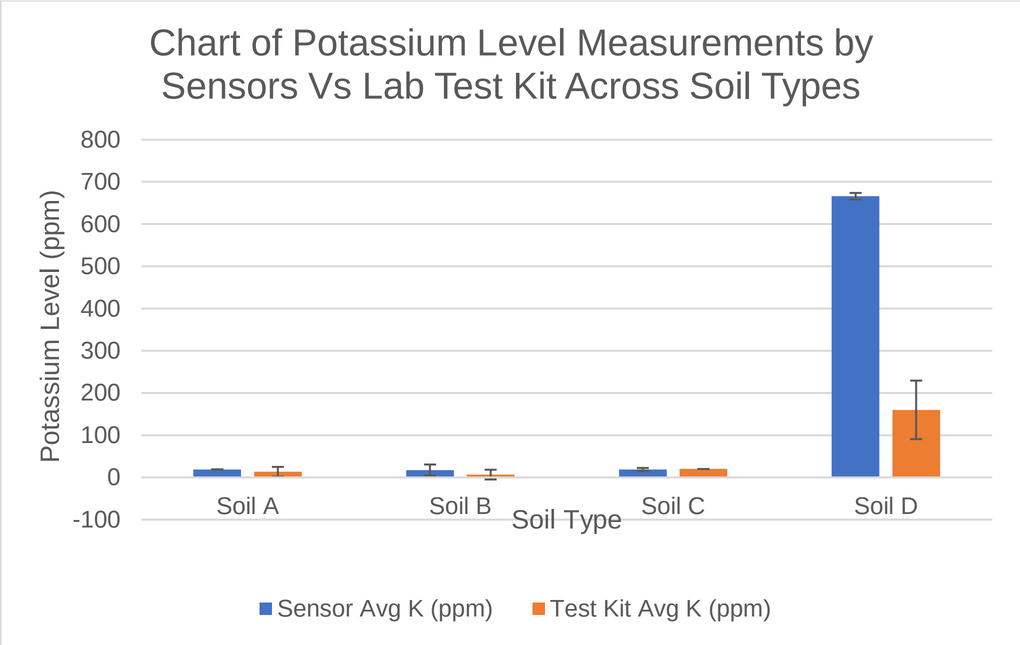


Figure 32: Chart of Potassium Level Measurements by Sensors Vs Lab Test Kit Across Soil Types

7.5 Rock Detection Testing

To evaluate the effectiveness of the rock detection system in the ASA, a series of controlled actuator tests were carried out. These tests involved moving the actuator under various conditions (air, soil, stone, and rock) while monitoring real-time current draw using the INA219 sensor. Tests were conducted at both 12V and 24V to determine how supply voltage affected the actuator response and sensitivity to resistance.

The goal was to establish clear current thresholds that differentiate between normal operation and obstruction due to rocks or hard soil.

7.5.1 Isolated Actuator Testing

The actuator was first tested in open air (no load) at 24V, to produce a baseline current profile as sheen in Figure 33. As shown in the first graph, the actuator maintained a steady draw of approximately 220–240 mA, with minimal fluctuation. Although a 12V version of this test was not captured, it is assumed based on actuator design and motor properties, that the air-load current at 12V would follow a similar trend, albeit slightly lower due to reduced torque. This baseline is critical for comparison, as it reflects minimal mechanical resistance and helps define the lower bound for obstruction-free operation.

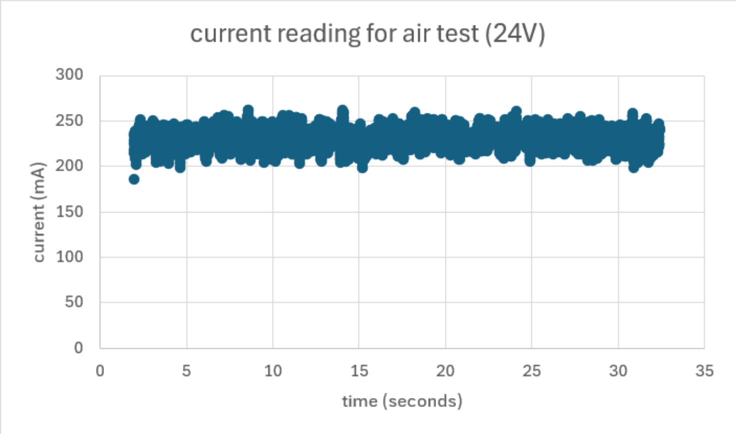


Figure 33 Isolated Actuator Test Results

7.5.2 Actuator Testing in Soil

The actuator was then tested in normal soil conditions at both 12V and 24V. The current remained relatively stable in the early phase of movement, averaging between 250–280 mA at 24V see Figure 34, and 220–260 mA at 12V, see Figure 35.

These tests demonstrated that loose or medium soil did not significantly impede the actuator or trigger false positives in the rock detection logic. However, the slow rise in current highlights the importance of using a rolling average to smooth out transitional behaviour without missing true obstruction events.

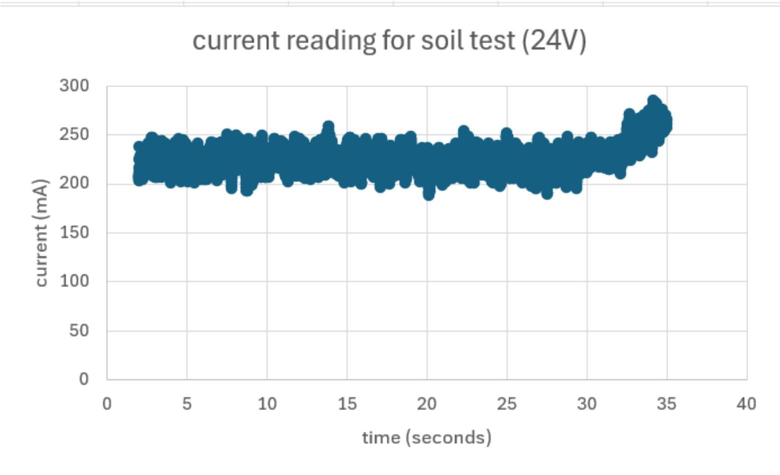


Figure 34: Actuator current test for soil (24V)

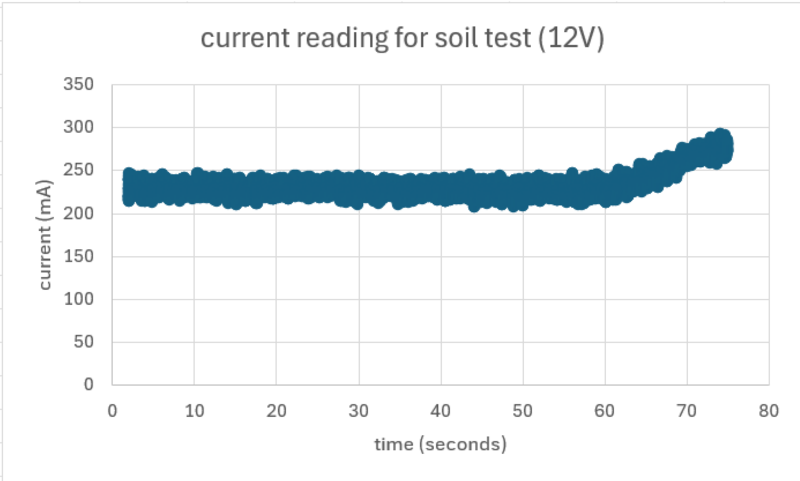


Figure 35: Actuator current test for soil (12V)

7.5.3 Actuator Testing on Stones

When deployed into soil containing small stones, the actuator exhibited slightly elevated currents. The current at 24V remained between 240–300 mA as shown in Figure 36, with a slight but consistent incline. At 12V, a similar pattern occurred, with values ranging from 260–360 mA as seen in Figure 37.

While these increases are notable, they were not abrupt. Instead, they reflected gradual increases in resistance rather than sudden blockage. These results indicate that small stones may not trigger the detection threshold depending on where the stone is in the soil and how it is orientated, which may lead to damage to the probes. This can be useful in refining the system for detecting partially obstructed zones.

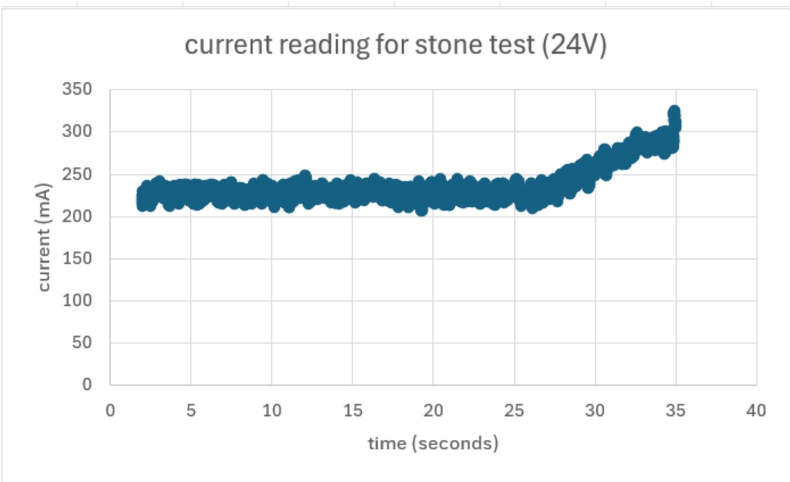


Figure 36 - Current Reading for Stone Test (24V)

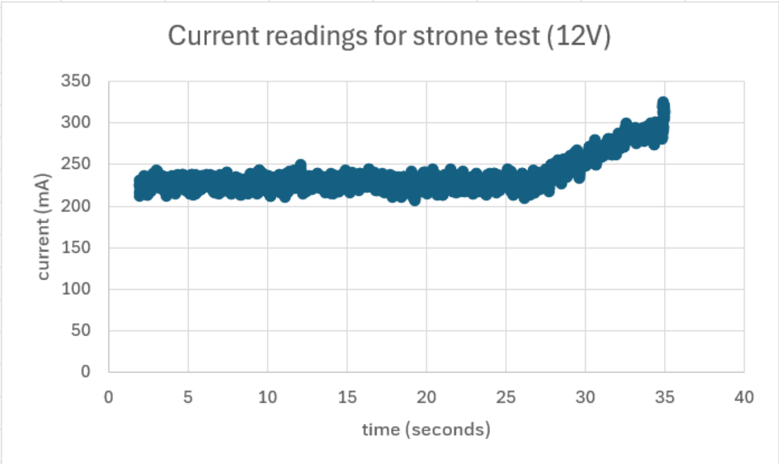


Figure 37 - Current Reading for Stone Test (12V)

7.5.4 Actuator Testing on Rocks

Rocks were introduced to simulate full obstruction. In both 12V and 24V scenarios, the current profile showed a sharp increase upon impact. At 24V, current spiked from ~250 mA to over 400 within a few seconds as seen in. At 12V, a similar behaviour was seen, with current exceeding 400 mA, clearly breaching the predefined detection threshold (350 mA). This sharp and sustained rise validates the effectiveness of the rock detection system. The threshold was reliably exceeded only during full obstructions, allowing the system to accurately trigger a retraction and repositioning event.

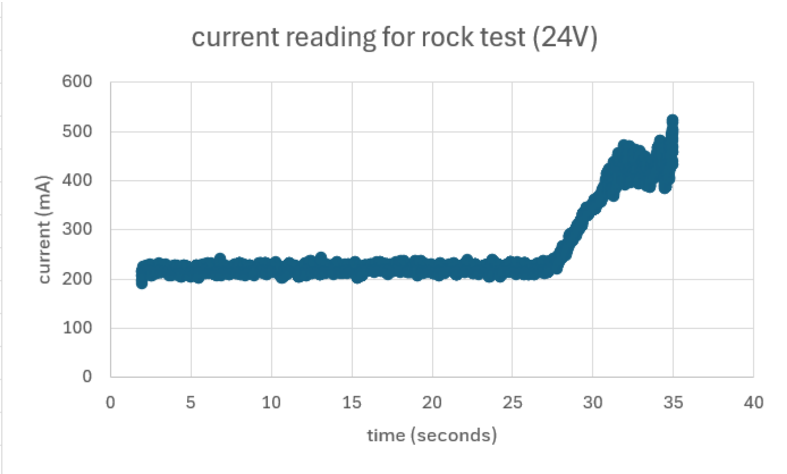


Figure 38 - current reading for rock test.

7.5.5 Overall results and conclusion

The testing conducted confirms that the actuator exhibits consistent resistance across its full stroke when operating with no load, such as in open air. When deployed into soil or small stones, the actuator generates a gradually increasing current profile, with noticeable changes in the gradient only once mechanical resistance is encountered. This behaviour could be leveraged in future iterations to distinguish between soft soil and harder materials, as a steeper current gradient suggests denser or more compacted ground potentially unsuitable for sensor insertion. This feature could also serve as an indicator of soil compaction levels, providing valuable agronomic insight. Additionally, the tests confirmed that rock contact results in sharp and sustained current spikes, clearly differentiating it from other soil conditions. This validates the system's ability to detect obstructions that may damage the sensor. The differences between soil, stones, and rocks across both 12V and 24V tests are clearly illustrated in Figure 39 and Figure 40, where the distinct current signatures for each condition are visible and consistent.

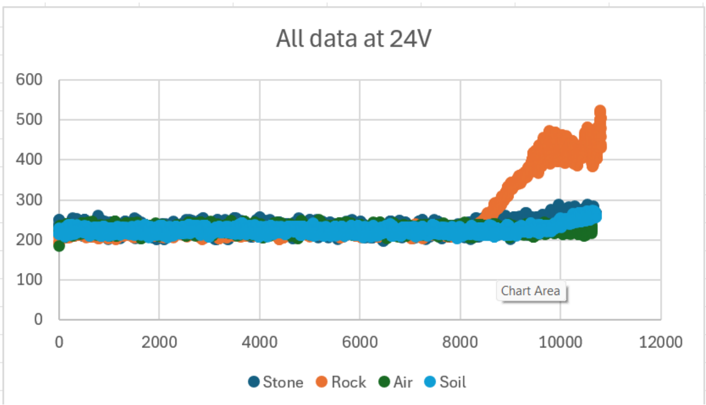


Figure 39: all data combined (24V)

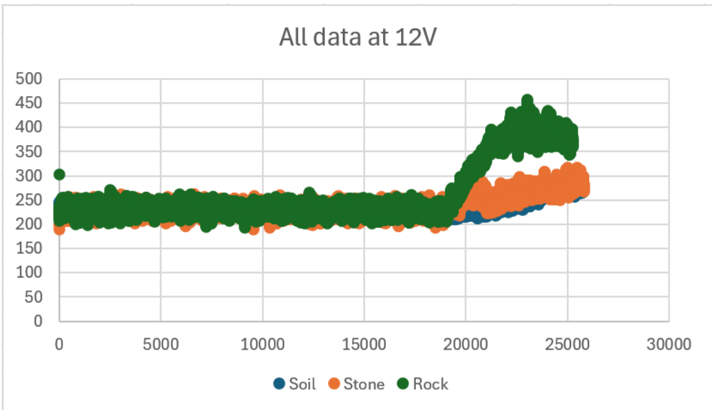


Figure 40: all data combined (12V)

The rolling average approach helped filter transient spikes while maintaining sensitivity to sustained obstructions. While missing the air test at 12V, assumptions based on the motor's consistent behaviour across voltages fill this gap without impacting conclusions.

An issue encountered during testing was the excessive number of current samples, which became evident only after plotting the data. This was due to the current sampling mechanism being placed inside a tight while loop without time regulation. As a result, thousands of samples were taken in a short period, leading to sampling jitter and potential data redundancy. This could have been mitigated by incorporating a timing mechanism such as using a fixed interval delay or a timestamp check within the loop to enforce consistent sampling intervals. Doing so would have also improved time-alignment between samples, simplified data analysis, and reduced unnecessary CPU usage during long-duration tests also allowing other processes to happen while the thread is sleep.

Overall, the actuator-based rock detection system performs reliably under both voltage conditions and provides clear, measurable indicators to support autonomous soil probing without risking sensor damage.

8 Evaluation

8.1 Computer Vision Performance

The computer vision software used in the classifier application provided high-confidence plant identification with high accuracy. BioClip [18] enabled the use of custom classes for identification as well as specific species predictions. It performed well, achieving 90% accuracy and an average confidence score of 54%. The performance of the computer vision software declined when multiple plants were present in the image, although it still maintained good accuracy. When a plant species had multiple types, the classifier often struggled or produced incorrect results due to the similarity between closely related species. Overall, if the camera is properly set up and captures images under optimal conditions, the computer vision system performs very well.

8.2 Sensor Performance

The sensor suite implemented in the ASA demonstrates strong potential for real-time, in-field monitoring of key soil health metrics. Across all soil types tested, the moisture and temperature sensors showed consistent and responsive behaviour, with low variability and good agreement with reference measurements. While some variability was observed in heterogeneous or loosely packed soils, especially in moisture and thermal readings, the sensors reliably reflected the expected physical behaviour of the materials. The pH and electrical conductivity sensors offered stable outputs suitable for continuous monitoring, though the lack of a robust comparative benchmark for EC and the slight under-reading of pH in complex soils suggest that periodic calibration or correction factors may improve long-term accuracy.

Among the nutrient sensors, nitrogen and phosphorus showed the most promising results in terms of consistency and the ability to distinguish between nutrient-poor and nutrient-rich soils. These sensors outperformed traditional colorimetric kits by providing objective, high-resolution data without the subjectivity inherent in visual interpretation. Potassium readings were also reliable at low to moderate concentrations but tended to overestimate in highly fertile soils, highlighting a need for calibration against known standards in those ranges. Overall, the sensors provide a highly effective platform for precision agriculture, with robust real-time data collection that supports targeted soil management, though some limitations in extreme or complex soil conditions warrant further testing and refinement.

8.3 Actuator Performance

The actuator system functioned reliably and as intended throughout testing, successfully enabling the ASA to probe the ground, detect obstacles, and withdraw when necessary. The integration with the INA219 current sensor provided effective feedback for rock detection, and the actuator control code performed consistently across repeated test cycles.

However, the system would have benefitted from ground compaction measurements. This could have been achieved through the integration of a force sensor, which would allow the system to quantify resistance encountered by the actuator more precisely. Such data would enhance the accuracy of soil classification and enable smarter decision-making regarding probe deployment this data could also be fed back to the farmers to help them better understand their land and make better decisions.

The custom 3D-printed actuator mounts provided a low-cost, adaptable, and effective solution for initial development and testing. They allowed for fast prototyping and accurate alignment, which was essential during early stages. However, during extended testing the mounts began to show signs of mechanical degradation, such as flexing and minor cracking. This was likely due to the repeated application of high axial loads beyond what standard PLA+ is rated for with a tensile strength of 61Mpa.

8.4 System Integration Performance

The Autonomous Soil Analyser (ASA) successfully demonstrated a high degree of integration across all hardware and software subsystems. The Raspberry Pi 5 served as a reliable central controller, effectively managing multiple processes simultaneously, including sensor polling, actuator control, and image capture via the USB-connected camera. Sensor communication through the RS485-to-USB adapter functioned as expected, with all soil parameters returning consistent data following the recommended stabilisation delay. The actuator control loop, driven via H-bridges and INA219 current feedback, enabled automated soil probing with basic obstacle detection, while image capture ran in parallel using multithreading. The system also performed well under load, aided by active cooling of the Pi 5, and the modular Python-based architecture facilitated straightforward integration of hardware components and libraries.

Despite the generally successful integration, several limitations were observed. The camera thread occasionally froze during long monitoring runs, sometimes destabilising the OS and requiring a reboot. There were also intermittent detection issues with the external hard drive, which, while useful for bulk data storage, proved less reliable in a field-ready configuration. Additionally, the current sensing system used to detect subsurface obstacles occasionally triggered false positives, halting soil probing prematurely. More significantly, the system was not able to autonomously operate from the RTU's internal battery due to hardware interfacing issues, requiring wall-plugged power supplies for testing. Finally, integration of the RTU's GPS module was incomplete, preventing automated geotagging of sensor and image data, which limits full deployment of the ASA as a precision mapping tool. These issues highlight areas for future refinement, but do not detract from the overall success of the core sensor integration and automation functionality.

8.5 User Interface Performance

The user interface was well built and displayed all data accurately with customisable parameters. Each aspect of the soil data was presented correctly and clearly, maintaining the application's user-friendly nature. Similarly, the plant identification feature displayed all relevant data as intended, with helpful pop-up elements to show plant information. Streamlit [19] was used for the application and proved easy to work with, offering useful visual features. The only notable drawback of the application was that the plant map became slow when loading large datasets. This was managed effectively in the code, but an alternative platform could be considered to improve performance when handling larger volumes of data.

8.6 Cost and Scalability

The ASA system demonstrates that a comprehensive soil monitoring platform can be developed on a relatively modest budget, with 88.6% of the allocated £1200 spent and most components used effectively. 76% of the purchased items were directly useful in the final build, and only 13.8% remained unused. This reflects strong cost efficiency overall. However, the budget could have been better optimised through earlier consolidation of component choices and clearer identification of redundant items during the procurement phase. Components that were never integrated represented sunk cost that offered no direct benefit to development or testing.

While the system is scalable in principle due to its modular construction and use of widely available parts, practical scalability may be limited by hardware reliability and integration complexity. The reliance on consumer-grade components, such as the external hard drive and USB interfaces, introduced issues including data loss, occasional peripheral disconnections, and damage to components when integrating them together. These issues raise concerns about long-term robustness in larger deployments or harsh environments.

Furthermore, while the Pi 5 proved capable of managing all system operations, its limited industrial protections and occasional software instability (such as camera thread freezing) highlight challenges in scaling from prototype to field-ready product. Addressing these issues will be key for improving system reliability at larger scales or in commercial use.

9. Future Development

9.1 Computer Vision Improvements

While using BioClip [18] worked well, our application required the ability to identify multiple plants within a single image. Additionally, the images captured often included numerous background elements, which the software would need to handle effectively. In light of this, a change in the image classification approach would be implemented. Rather than processing the entire image at once, it would be divided into smaller sections to improve accuracy and increase tolerance to the presence of multiple plants. A further step to extract and highlight key information for display could then be integrated into the visualisation tool. Due to BioClip's high accuracy and its training on the largest dataset of plants and wildlife, it would remain the classifier of choice.

9.2 Sensor Improvements

While the integrated 7-in-1 ComWinTop soil sensor provided a convenient and compact method for capturing a broad range of soil parameters, there are several opportunities for improvement in future iterations of the ASA system. Firstly, more rigorous calibration and refinement of the testing protocol could help establish sensor-specific baselines and correct for soil-type variations, particularly in parameters like potassium and pH where deviations were observed. In terms of hardware, replacing the all-in-one sensor with a set of specialised, independently calibrated sensors could improve accuracy and long-term reliability. Dedicated probes for pH, electrical conductivity, or moisture may outperform bundled sensors in terms of sensitivity and degradation resistance, particularly under harsh environmental conditions. The pH sensor is observed to corrode faster than the other probes, meaning that a dedicated pH probe would be far easier to replace without discarding the entire system, enhancing maintainability. It would also allow for more flexible sensor placement or redundancy, improving data accuracy through cross-verification.

Future development could also incorporate self-cleaning or protective housing for sensors to reduce fouling, especially in clay-rich or organic-heavy soils as the sensor readings are dependent on probe surface area that is covered. Finally, integrating real-time calibration routines or machine learning-based correction algorithms using historical soil profiles could further enhance measurement precision and adaptability across varied field conditions. These changes would collectively support a more robust, scalable, and accurate sensing framework for precision agriculture applications.

9.3 Actuator Enhancements

While the linear actuator system operated effectively during testing, several improvements have been identified to enhance its durability, functionality, and adaptability in future versions of the ASA.
Incorporating a force sensor would allow the system to quantify the resistance experienced during soil probing. This would provide accurate data on soil compactness, enabling the ASA to make better-informed decisions about whether a probing site is suitable, and helping generate more detailed agronomic profiles.

The current 3D-printed actuator mounts, while lightweight and easy to prototype, began to degrade under repeated mechanical stress during testing. Future designs should utilise more robust materials such as reinforced PETG, carbon-fibre composites, or aluminium to extend operational lifespan and maintain performance under load.

The obstacle detection mechanism could be improved by increasing the number of probes that penetrate the ground for rocks, this increase in area can allow for more error in the movement of the RTU.
To prevent damage to the sensors themselves, future iterations of the sensor mount could feature breakaway or deformable safety mechanisms. These would allow the mount to yield or detach if excessive force is applied, absorbing the impact and preventing sensor breakage as sensors can be costly and time consuming to replace.
Future development should also consider a more modular and scalable architecture, allowing the actuator system to be easily mounted on a range of mobile platforms beyond the Robotriks RTU. This includes integration onto tractors, quad bikes, or autonomous rovers, supporting broader deployment in diverse agricultural or environmental monitoring contexts.

By implementing these improvements, the actuator system would become more intelligent, adaptable, and robust supporting reliable, autonomous operation at scale and across varied terrain.

9.4 Integration and Enhancement

While the Raspberry Pi 5 and Python-based integration have performed well, there are several areas for improvement. Upgrading the external storage from a USB hard drive to a solid-state drive (SSD) would enhance data reliability, speed, and durability, especially for extensive field use.

Expanding the system with multiple directional cameras would provide broader coverage for environmental monitoring and weed detection, improving data accuracy. These cameras could be integrated via additional USB ports or dedicated modules like the Raspberry Pi Camera Module.

Improving GPS data integration could be achieved by incorporating a 433 MHz radio module to wirelessly transmit coordinates from the RTU to the ASA, offering more reliable communication compared to current methods. This would enhance real-time geospatial tracking and system stability.

Lastly, adopting a more robust Python framework or exploring a real-time operating system (RTOS) could help manage the increasing complexity of tasks, improving reliability and responsiveness for larger datasets and demanding environments.

9.5 Deployment Considerations and Scalability

For future deployment, accessing RTU power autonomously remains a key improvement area. Integrating a more efficient power management system to draw directly from the RTU's power source would eliminate reliance on external power supplies, making the system truly autonomous for field use. Additionally, enhancing the system's modularity would allow the ASA to be used on various mobile platforms, not just the RTU. This would provide farmers with the flexibility to deploy the system on different vehicles or even handheld units, increasing the system's accessibility and adaptability. This could involve designing a universal mount or integration kit, enabling seamless transfer between machines without requiring major adjustments to hardware or software.

The development of a modular, scalable system for the ASA opens up opportunities to reduce costs and improve accessibility. By designing components that can be easily integrated into different mobile platforms, the system can cater to various farm sizes and budget constraints. This flexibility ensures that smaller farms with limited resources can still benefit from the technology by using a more affordable, lightweight version of the system. Furthermore, as the demand for precision agriculture grows, scaling the system to accommodate larger fields or more complex applications can be achieved through cost-effective upgrades. For instance, using open-source software and readily available hardware components can significantly reduce production costs while enabling farmers to adopt the system at a lower price point. This scalability and cost efficiency would allow broader adoption across the agriculture sector.

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11. Appendices

11.1 Appendix A – Arable weeds for classification

The bellow list shows the list of arable weeds obtained from the encyclopaedia of arable weeds [2].

Annual meadow-grass, Awned canary-grass, Barley, Barren brome, Black bent, Black-bindweed, Black-grass, Black mustard, Black nightshade, Broad-leaved dock, Canadian fleabane, Charlock, Cleavers, Cock’s-foot, Common chickweed, Common couch, Common field-speedwell, Common fumitory, Common hemp-nettle, Common mouse-ear, Common nettle, Common orache, Common poppy, Corn spurrey, Cornflower, Cow parsley, Creeping bent, Creeping thistle, Crested dog’s-tail, Curled dock, Cut-leaved crane’s-bill, Daisy, Dandelion, Dove’s-foot crane’s-bill, Fat hen, Field bean, Field bindweed, Field forget-me-not, Field horsetail, Field pansy, Fool’s parsley, Garlic mustard, Great brome, Green field-speedwell, Groundsel, Hedge mustard, Hemlock, Henbit dead-nettle, Italian rye-grass, Ivy-leaved speedwell, Knapweed, Knot-grass, Linseed, Long-headed poppy, Loose silky bent, Meadow brome, Nipplewort, Oat, Oilseed rape, Onion couch, Pale persicaria, Parsley-piert, Pea, Perennial rye-grass, Perennial sow-thistle, Pineappleweed, Potato, Prickly sow-thistle, Ragwort, Red dead-nettle, Red fescue, Redshank, Rough-stalked meadow-grass, Round-leaved fluellen, Rye brome, Scarlet pimpernel, Scented mayweed, Scentless mayweed, Sharp-leaved fluellen, Shepherd’s-needle, Shepherd’s-purse, Small nettle, Smooth sow-thistle, Soft brome, Spear thistle, Spreading hedge-parsley, Sugar beet, Sunflower, Timothy, Venus’s-looking-glass, Wall speedwell, Wheat, White campion, Wild carrot, Wild-oat, Wild pansy, Wild radish, Winter wild-oat, Yorkshire-fog, Gorse, Hawthorn

11.2 Appendix B – Meeting Record

Meeting	Date	Time	Duration	Location	Attendees	Last meeting minutes/progress review	Meeting Agenda	What was achieved/Problems that have arisen	Goals to be complete before next meeting
1	28/01/2025	13:00:00	1 hour	Smeaton 307	Luke, Sayeed, Rhys	N/A	• Discuss parts required for project • Discuss subsequent budget adjustments if necessary • Discuss timeline for purchases • Order first lot of parts • Discuss where we are with current plan and what needs to be before the next meeting	• Everything stated in the agenda was achieved • Slight change to budget	• Luke to start getting documentation ready and look into data processing • Sayeed to continue ordering parts and look into different options • Rhys to look start looking into getting the linear actuator working Next meeting scheduled for 30/01/2025 at 13:00 in Smeaton 307
2	30/01/2025	13:00:00	0.5 hours	Smeaton 307	Luke, Sayeed, Rhys	• Some issues with ordering process with alternatives needing to be found • Majority of parts ordered • Documentation laid our and prepared • Actuator working with additional parts to be ordered	• Ensure all parts required at this time are ordered and processed • Recap on documentation that needs to be done periodically • Ensure we are adhering to plan and organize work for following meeting	• A new set of components found and ordered in line with Smeaton stores purchasing requirements. • A plan made to commence work on individual responsibilities	• Luke to start getting code together for data processing in particular plant identification • Sayeed to finish part ordering and look into getting the Raspberry Pi set up • Reece to order parts for actuator and begin getting them functional Next meeting scheduled for 11/02/2025 at 13:00 in Smeaton 307 no meeting on 06/02/2025 due to external commitments of members
3	11/02/2025	13:00:00	1 hour	Smeaton 307	Luke, Sayeed, Rhys	• Code working to take a file of images and extract all relevant information and run through classification/class training • Simple app design for visualisation of data to be updated • All parts currently required ordered except H-bridge to be done in meeting	• Discus progress of individual tasks • Get final parts together and organise acquiring H-Bridge • Demonstration of data Processing and format for app integration	• All parts currently required ordered • Feedback on data processing and app • Git hub set up • Some parts acquired that had arrived and tested	• Luke to act on code feedback and update documentation • Reece to get actuators fully functional • Sayeed to get Raspberry pi working and investigate any parts that have arrived Deliverables to be met by 18/02/2025 but next meeting scheduled for 13/02/2025 at 15:00 in Smeaton 307 to update Paul on progress
4	13/02/2025	13:00:00	2 hour	Smeaton 307	Luke, Sayeed, Rhys, Paul	N/A	• Updating Paul of progress	• Feedback on current progress	• Luke to update code and processing with colour code symbols and multiple plant detection. Luke also to get Spec and purchase camera •Sayeed to get sensor working and saving data to the hard drive • Reece to get functional actuator with current sensors controlled by the raspberry Pi
5	20/03/2025	11:00:00	1.5 hour	Smeaton 307	Luke, Sayeed	• Discussed and demonstrated up to date code	• To get code and text file formatting the same • To test the Soil sensors Function • Discuss how we move forwards	• code and text file formatting the same • Tested the Soil sensors Function • Discussed how we move forwards	• Luke to update web app with soil data. Have a option to display both probes or one or the other. hover over area and display values. graphs etc • Sayeed to continue working on getting soil sensors working with the Raspberry Pi and sort out coordination with Rhys actuators Progress meeting with Paul scheduled for 25/03/2025 at 11:00 in Smeaton 307
6	25/03/2025	11:00:00	1 Hour	Smeaton 307	Luke, Sayeed, Rhys, Paul	N/A	• Updating Paul of progress	• Feedback on current progress	• Luke to get test data on the camera positioning and best fits • Sayeed to get test data on soil sensors and test on different types of soil • Rhys to get test data on soil firmness and possibly order a different actuator • All to order test supplies and more raspberry pies
7	27/03/2025	10:00:00	4 hours	Smeaton 307 + 303B	Luke, Sayeed, Rhys	• Due to closeness of meetings no further actions have been taken	• Collect parts • Set up raspberry pies • Get a plan for the holiday period	• Plan for holidays achieved • Raspberry pies set up • Rut Scaffolding complete • Parts ordered	• Luke to get testing sorted and keep documentation up to date. Also to start report and design back panel for box. Developed code to take periodic images • Sayeed to get testing done on soil sensors and collect data • Rhys to organise RTU and start mounting actuators. Also to start testing on soil compression
8	15/04/2025	10:00:00	4 hours	Smeaton 303B	Luke, Sayeed, Rhys	• Luke has completed part of the report and got test data for the camera with finding written up but not yet added data. Back plate has been made but may need redesign. Camera code is complete to take periodic images with the Pi • Sayeed has gathered test data for majority of soil parameters and has tabulated results. • Rhys has began to mount actuators and gathered readings ready to incorporate test data. Also got the RTU built in the labs ready.	• To start to get the project working as one unit • get a plan for the following weeks leading to the deadline • Continue testing and collecting results • Complete and update documentation	• Continued documentation and report update • started to get things attached to the RTU • Continued to get test results • Rtu fitted with all fixtures	• All to continue working together on points discussed Daily
9	16/04/2025	10:30:00	5 hours	Smeaton 303B	Luke, Sayeed, Rhys	• Rtu fitted with components and set up in labs with all fixtures • Testing results continued to be collected	• Finish off soil testing • Get rock detection working • Continue to intergrade system • Order and design power from the RTU	• Continued documentation • Ordered connectors for power • Continued to get test results	• All to continue working together on points discussed Daily

10	17/04/2025	11:00:00	4 hours	Smeaton 303B	Luke, Sayeed, Rhys	• Majority of testing complete •Rock detection complete • Documentation updated	• Get code working as 1 unit on the pi • Get Test results written up • Test rock detection under different conditions • Interface with the RTU	• Test results written up to date • SSH and VNC viewer working on pies to make interfacing easier • Poster and abstract started • Code to get gps from the RTU done • Code started for system wide functions	• All Documentation + abstract and poster to be done over the weekend • Further testing to be completed for missing results
11	22/04/2025	11:00:00	5 hours	Smeaton 303B	Sayeed, Rhys	• Poster and abstract submitted • Further camera testing done • updated code for the web app	• Continue to complete system integration	• Feedback from Jake • continued system integration • Fitted new sensor mount	• All to continue working together on points discussed Daily
12	23/04/2025	11:00:00	5 hours	Smeaton 303B	Sayeed, Rhys	• Progress made on system integration • Ordered power connectors	• Continue to complete system integration	• Code for system implemented onto to the pi	• All to continue working together on points discussed Daily
13	24/04/2025	12:00:00	4 hours	Smeaton 303B	Luke, Sayeed, Rhys	• Update on progress in Lukes absence	• Continue to complete system integration • Update all documentation • Get RTU interacting • Order, design and build power system	• Code for system implemented onto to the pi including camera • Documentation updated and test results added to report • Radio transceiver ordered Box back plates and mounting designed and sent to 3d print • started to script ted talk • organised Viva	• All to continue working together on points discussed Daily
14	25/04/2025	10:30:00	5 hours	Smeaton 303B	Luke, Sayeed, Rhys	• No progress over night	• Make up and connect power circuit • Get receiver fitted to pi • Film Ted talk • Continue report write up and documentation • Get all components into enclosure, fitted and neat	• Ted talk filmed and voice overs recorded • More progress on report and other documentation • Enclosures almost together • Testing	• Rhys and Syeed t get video edited and last bits of the box together and soldered • Luke to get Report and documentation of testing data done plus optimise and finalise both apps.
15	28/04/2025	09:30:00	6 Hours	Smeaton 303B	Luke, Sayeed, Rhys	• Luke has optimised and finalised classifier and app. Plus added substantial content to report. Testing completed and shown in excel documents. • Rhys has almost finished Ted talk editing and has box fitted and soldered • Sayeed helped Rhys with editing	• Get all components together and mounted neatly • Ensure all code is working as on the RTU • Connect power up if connectors arrive • Connect radio addition up if it arrives • Continue documentation	• Issues with broken components meant spending the whole day trying to fix the system and get everything mounted. • Video finalised and submitted • Any spare time spent preparing documentation	• Rhys to finish video editing and submit • Luke to take home broken components and fix them
16	29/04/2025	09:00:00	6 Hours	Smeaton 303B	Luke, Sayeed, Rhys	• Luke has fixed the h-bridge • Rhys has finished Ted talk	• Get everything in the enclosure, attached to power and working as a unit. • Complete Viva	• System working as a whole • Viva completed	• All to finish report
17	01/05/2025	09:30:00	5 Hours	Smeaton 303B	Luke, Sayeed, Rhys	N/A	• Showcase	• Showcase	• All to finish report

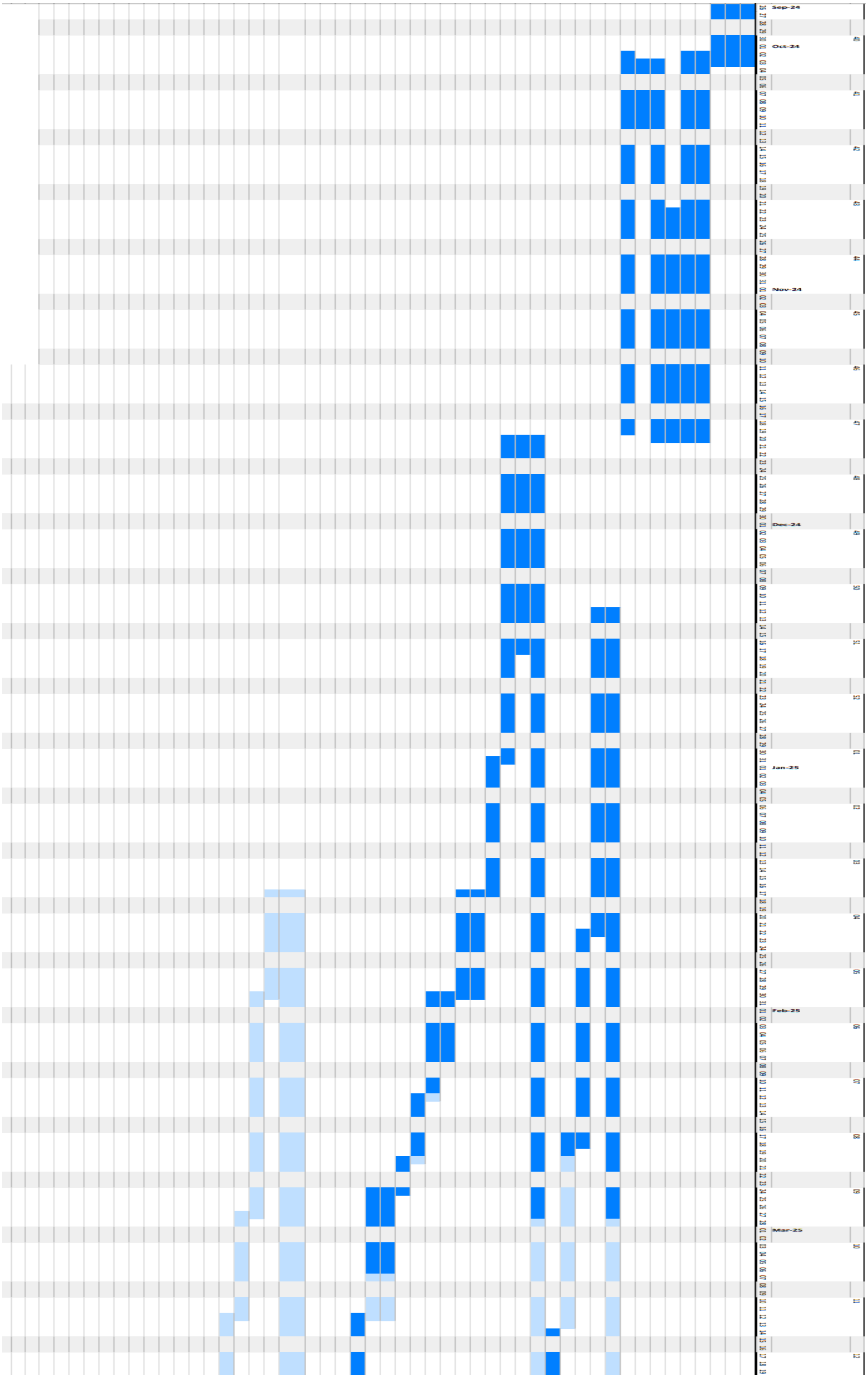
11.3 Appendix C – Gantt Chart

PROJ515 **74%**

University of Plymouth

Monday 5 May 2025

WBS	Task Names	Resource Names:	Start	Duration	Finish	% Complete	Calendar days	Days Completed	Days Remaining
			26-Sep-2024	130	26-Mar-2025	74%	182		
0	**Moblie Soil Analyser**	**RJ, SR, LQ**	**26-Sep-2024**	**40**	**20-Nov-2024**	**74%**	**56**	**0**	**0**
1	**Project Formation**	**RJ, SR, LQ**	**26-Sep-2024**	**6**	**03-Oct-2024**	**100%**	**8**	**0**	**0**
1.1	Discuss individual strenghts	RJ, SR, LQ	26-Sep-2024	6	03-Oct-2024	100%	**8**	**0**	**0**
1.2	Discuss deliverables of the project (project scope)	RJ, SR, LQ	26-Sep-2024	6	03-Oct-2024	100%	**8**	**0**	**0**
2	**Project Design**	**RJ, SR, LQ**	**02-Oct-2024**	**36**	**20-Nov-2024**	**100%**	**50**	**0**	**0**
2.1	PEP	RJ, SR, LQ	02-Oct-2024	36	20-Nov-2024	100%	**50**	**0**	**0**
2.2	IP Landscape	RJ, SR, LQ	22-Oct-2024	22	20-Nov-2024	100%	**30**	**0**	**0**
3	**Research**	**RJ, SR, LQ**	03-Oct-2024	35	20-Nov-2024	100%	**49**	**0**	**0**
3.1	Meeting with Jake	RJ, SR	03-Oct-2024	7	11-Oct-2024	100%	**9**	**0**	**0**
3.2	Project Component Research	RJ, SR, LQ	02-Oct-2024	35	19-Nov-2024	100%	**49**	**0**	**0**
4	**COMPUTER VISION**	**LQ**	**12-Dec-2024**	**71**	**20-Mar-2025**	80%	**99**	**0**	**0**
4.1	Set up Bioclip on an MCU	LQ	12-Dec-2024	30	22-Jan-2025	100%	**42**	**0**	**0**
4.2	Train Detection for Ragwort	LQ	22-Jan-2025	20	18-Feb-2025	100%	**28**	**0**	**0**
4.2	Train Detection to Count for Biodiversity	LQ	16-Feb-2025	20	13-Mar-2025	20%	**26**	**0**	**0**
4.3	Combine Processes into an Efficient Package with UI	LQ	14-Mar-2025	5	20-Mar-2025	100%	**7**	**0**	**0**
5	**Hardware & Software Development**	**RJ, SR, LQ**	**20-Nov-2024**	**91**	**26-Mar-2025**	**80%**	**127**	**0**	**0**
5.1	Further Research into Sensors	RJ, SR	20-Nov-2024	20	17-Dec-2024	100%	**28**	**0**	**0**
5.2	Order Components	RJ, SR	20-Nov-2024	30	31-Dec-2024	100%	**42**	**0**	**0**
5.3	Test Components	RJ	31-Dec-2024	14	17-Jan-2025	100%	**18**	**0**	**0**
5.4	Develop and Prototype Sensor Mounts	LQ, SR, RJ	17-Jan-2025	10	30-Jan-2025	100%	**14**	**0**	**0**
5.5	Write Drivers for Sensors and Actuators	RJ, SR	17-Jan-2025	10	30-Jan-2025	100%	**14**	**0**	**0**
5.6	Test Hardware with Drivers	RJ, SR	30-Jan-2025	7	07-Feb-2025	100%	**9**	**0**	**0**
5.7	Calibrate Hardware	RJ, SR	30-Jan-2025	10	12-Feb-2025	90%	**14**	**0**	**0**
5.8	Use Sensors to Measure and Compare to Lab Results	RJ, SR, LQ	12-Feb-2025	7	20-Feb-2025	86%	**9**	**0**	**0**
5.9	Evaluate a Margin of Error	RJ, SR, LQ	20-Feb-2025	3	24-Feb-2025	100%	**5**	**0**	**0**
5.10.	Adapt System to RTU	RJ, SR, LQ	22-Feb-2025	14	12-Mar-2025	75%	**19**	**0**	**0**
5.11	Further Lab Testing to Adjust Sensors to Work on Site	RJ, SR, LQ	22-Feb-2025	14	12-Mar-2025	75%	**19**	**0**	**0**
5.12	Finalise Prototype Design	RJ, SR, LQ	12-Mar-2025	7	20-Mar-2025	90%	**9**	**0**	**0**
5.13	Interface System with RTU	RJ, SR, LQ	20-Mar-2025	3	24-Mar-2025	25%	**5**	**0**	**0**
5.14	Controlled Field Test	RJ, SR, LQ	23-Mar-2025	3	25-Mar-2025	35%	**3**	**0**	**0**
5.15	Field Test Passing Prototype Ready	RJ, SR, LQ	23-Mar-2025	3	25-Mar-2025	25%	**3**	**0**	**0**
6	**Automation of cleaning the probes and soil compaction**	**RJ, LQ**	**17-Jan-2025**	**48**	25-Mar-2025	0%	**68**	**0**	**0**
6.1	Decide on Probe Cleaning Method	RJ, LQ	17-Jan-2025	10	30-Jan-2025	0%	**14**	**0**	**0**
6.2	Prototype and Design Cleaning Components	RJ, LQ	30-Jan-2025	21	27-Feb-2025	0%	**29**	**0**	**0**
6.3	Test and Develop Cleaning Method	RJ, LQ	27-Feb-2025	10	12-Mar-2025	0%	**14**	**0**	**0**
6.4	Implement into Overall System	RJ, SR, LQ	12-Mar-2025	10	25-Mar-2025	0%	**14**	**0**	**0**
7	**Integration**	**RJ, SR, LQ**	**20-Mar-2025**	**14**	**08-Apr-2025**	75%	**20**	**0**	**0**
7.1	Integrate CV with Sensors	RJ, SR, LQ	20-Mar-2025	7	28-Mar-2025	100%	**9**	**0**	**0**
7.2	Integrate Full System with RTU	RJ, SR, LQ	23-Mar-2025	7	31-Mar-2025	25%	**9**	**0**	**0**
7.3	Field Testing	RJ	01-Apr-2025	2	02-Apr-2025	50%	**2**	**0**	**0**
7.4	Check and Evaluate Data	SR, LQ	02-Apr-2025	2	03-Apr-2025	**100%**	**2**	**0**	**0**
7.5	Create Heatmap of Data	LQ	03-Apr-2025	4	08-Apr-2025	100%	**6**	**0**	**0**
8	**Refinement**	**RJ, LQ, SR**	**08-Apr-2025**	**18**	**01-May-2025**	**0%**	**24**	**0**	**0**
8.1	Create UI for the Data	LQ	08-Apr-2025	7	16-Apr-2025	100%	**9**	**0**	**0**
8.2	Process New Data into a Heatmap	LQ	08-Apr-2024	4	11-Apr-2024	100%	**4**	**0**	**0**
8.3	Further Field Testing With UI	RJ, SR, LQ	16-Apr-2025	5	22-Apr-2025	20%	**7**	**0**	**0**
8.4	Final Checks and Improvements	RJ, SR, LQ	17-Apr-2025	**7**	25-Apr-2025	**50%**	**9**	**0**	**0**
9	**End of project (Presentation)**	**RJ, SR, LQ**	**29-Apr-2025**	**4**	**02-May-2025**	100%	**4**	**0**	**0**



Sep-24
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